Advanced Scikit-Learn

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Me

universitätbonn ais

Amazon Machine Learning

NYU Center For Data Science

Classification
Regression
Clustering
Semi-Supervised Learning
Feature Selection
Feature Extraction
Manifold Learning
Dimensionality Reduction
Kernel Approximation
Hyperparameter Optimization
Evaluation Metrics
Out-of-core learning
……

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Overview

- Reminder: Basic scikit-learn concepts
- Working with text data
- Model building and evaluation:
  - Pipelines
  - Randomized Parameter Search
  - Scoring Interface
- Out of Core learning
  - Feature Hashing
  - Kernel Approximation
- New stuff in 0.17 and 0.18-dev
  - Overview
  - Calibration

scikit learn

Home Installation Documentation Examples

Google™ Custom Search Search ×

Documentation of scikit-learn 0.17

Quick Start

A very short introduction into machine learning problems and how to solve them using scikit-learn. Introduced basic concepts and conventions.

User Guide

The main documentation. This contains an in-depth description of all algorithms and how to apply them.

Other Versions

- scikit-learn 0.18 (development)
- scikit-learn 0.17 (stable)
- scikit-learn 0.16
- scikit-learn 0.15

Tutorials

Useful tutorials for developing a feel for some of scikit-learn's applications in the machine learning field.

API

The exact API of all functions and classes, as given by the docstrings. The API documents expected types and allowed features for all functions, and all parameters available for the algorithms.

Additional Resources

Talks given, slide-sets and other information relevant to scikit-learn.

Contributing

Information on how to contribute. This also contains useful information for advanced users, for example how to build their own estimators.

Flow Chart

A graphical overview of basic areas of machine learning, and guidance which kind of algorithms to use in a given situation.

FAQ

Frequently asked questions about the project and contributing.

http://scikit-learn.org/

Representing Data

$$X = \begin{pmatrix} 1.1 & 2.2 & 3.4 & 5.6 & 1.0 \\ 6.7 & 0.5 & 0.4 & 2.6 & 1.6 \\ 2.4 & 9.3 & 7.3 & 6.4 & 2.8 \\ 1.5 & 0.0 & 4.3 & 8.3 & 3.4 \\ 0.5 & 3.5 & 8.1 & 3.6 & 4.6 \\ 5.1 & 9.7 & 3.5 & 7.9 & 5.1 \\ 3.7 & 7.8 & 2.6 & 3.2 & 6.3 \end{pmatrix}$$

Representing Data

one sample

$$X = \begin{pmatrix} \boxed{1.1 & 2.2 & 3.4 & 5.6 & 1.0} \\ 6.7 & 0.5 & 0.4 & 2.6 & 1.6 \\ 2.4 & 9.3 & 7.3 & 6.4 & 2.8 \\ 1.5 & 0.0 & 4.3 & 8.3 & 3.4 \\ 0.5 & 3.5 & 8.1 & 3.6 & 4.6 \\ 5.1 & 9.7 & 3.5 & 7.9 & 5.1 \\ 3.7 & 7.8 & 2.6 & 3.2 & 6.3 \end{pmatrix}$$

Representing Data

one sample

$$X = \begin{pmatrix} 1.1 & 2.2 & 3.4 & 5.6 & 1.0 \\ 6.7 & 0.5 & 0.4 & 2.6 & 1.6 \\ 2.4 & 9.3 & 7.3 & 6.4 & 2.8 \\ 1.5 & 0.0 & 4.3 & 8.3 & 3.4 \\ 0.5 & 3.5 & 8.1 & 3.6 & 4.6 \\ 5.1 & 9.7 & 3.5 & 7.9 & 5.1 \\ 3.7 & 7.8 & 2.6 & 3.2 & 6.3 \end{pmatrix}$$

one feature

Representing Data

one sample

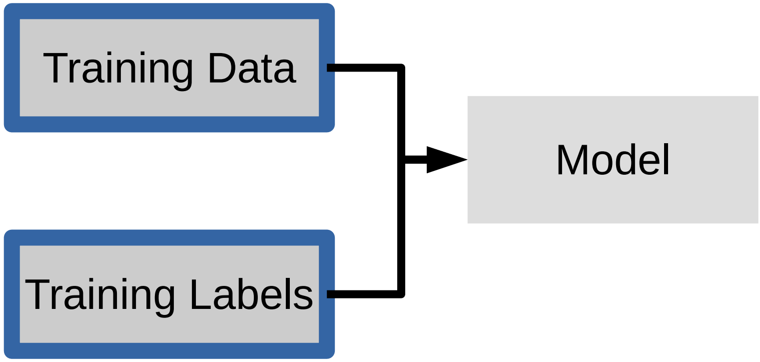
$$X = \begin{pmatrix} 1.1 & 2.2 & 3.4 & 5.6 & 1.0 \\ 6.7 & 0.5 & 0.4 & 2.6 & 1.6 \\ 2.4 & 9.3 & 7.3 & 6.4 & 2.8 \\ 1.5 & 0.0 & 4.3 & 8.3 & 3.4 \\ 0.5 & 3.5 & 8.1 & 3.6 & 4.6 \\ 5.1 & 9.7 & 3.5 & 7.9 & 5.1 \\ 3.7 & 7.8 & 2.6 & 3.2 & 6.3 \end{pmatrix} \qquad y = \begin{pmatrix} 1.6 \\ 2.7 \\ 4.4 \\ 0.5 \\ 0.2 \\ 5.6 \\ 6.7 \end{pmatrix}$$

one feature

outputs / labels

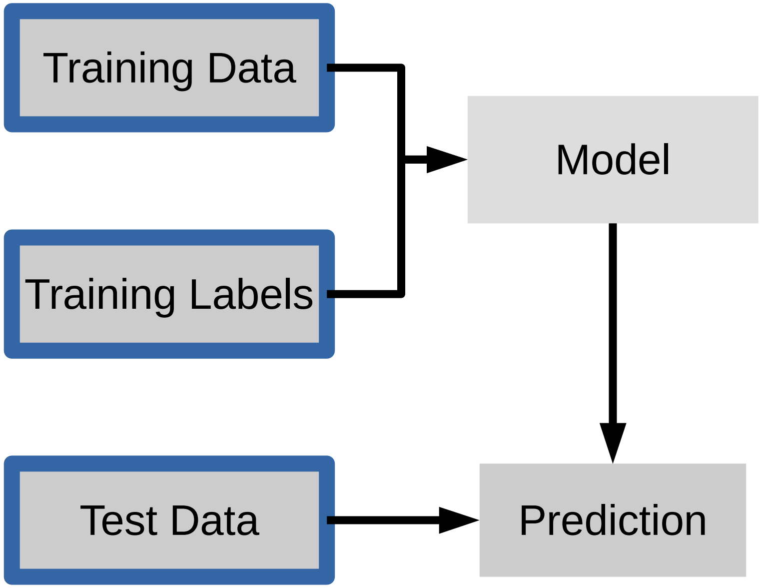
Supervised Machine Learning

```
clf = RandomForestClassifier()


clf.fit(X_train, y_train)
```



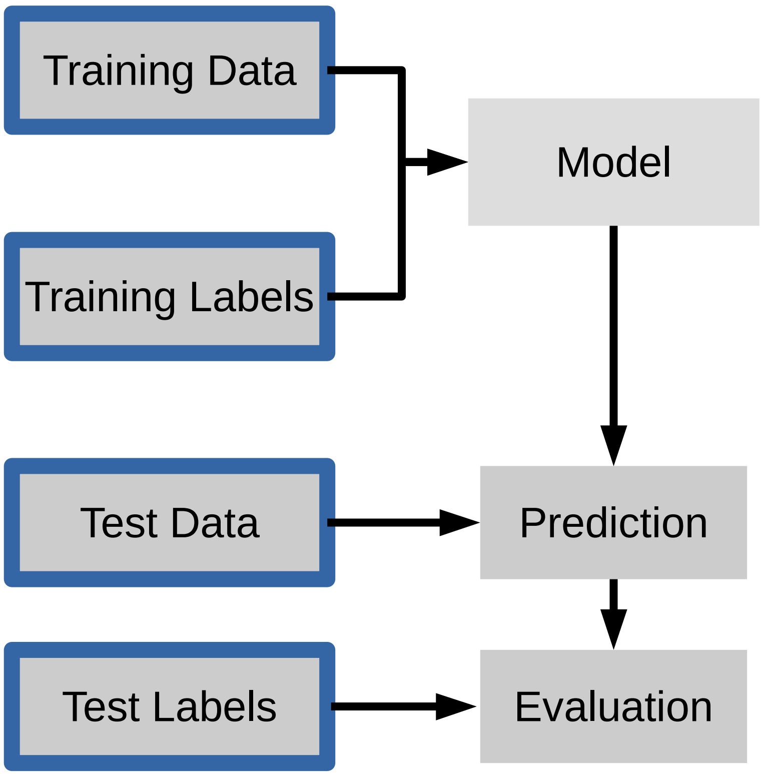
Supervised Machine Learning

```
clf = RandomForestClassifier()

clf.fit(X_train, y_train)

y_pred = clf.predict(X_test)
```



Supervised Machine Learning

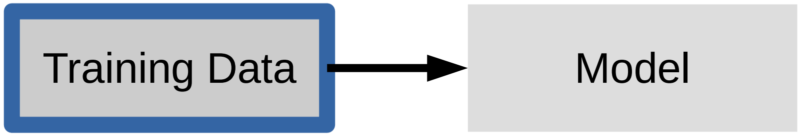
```
clf = RandomForestClassifier()

clf.fit(X_train, y_train)

y_pred = clf.predict(X_test)

clf.score(X_test, y_test)
```



Unsupervised Transformations

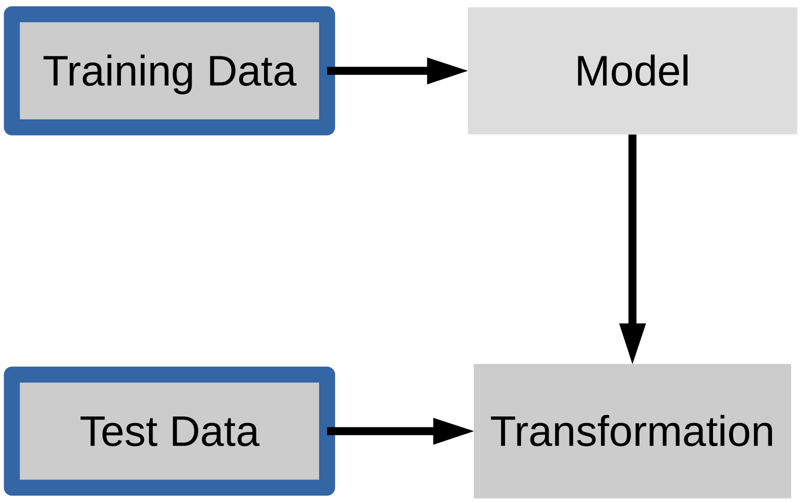
```
pca = PCA(n_components=3)
```

```
pca.fit(X_train)
```



Unsupervised Transformations

```
pca = PCA(n_components=3)

pca.fit(X_train)

X_new = pca.transform(X_test)
```



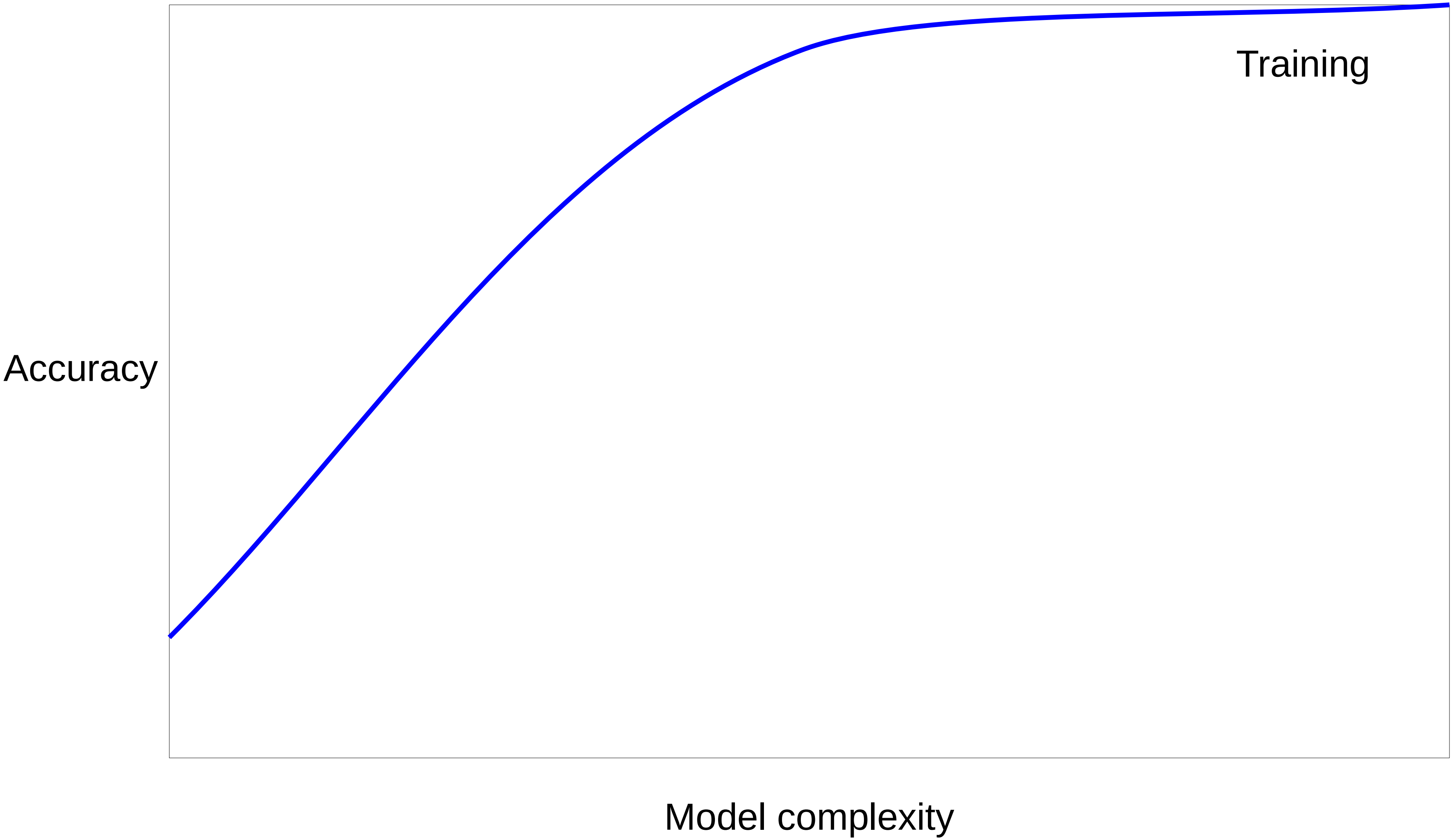
Basic API

`estimator.fit(X, [y])`

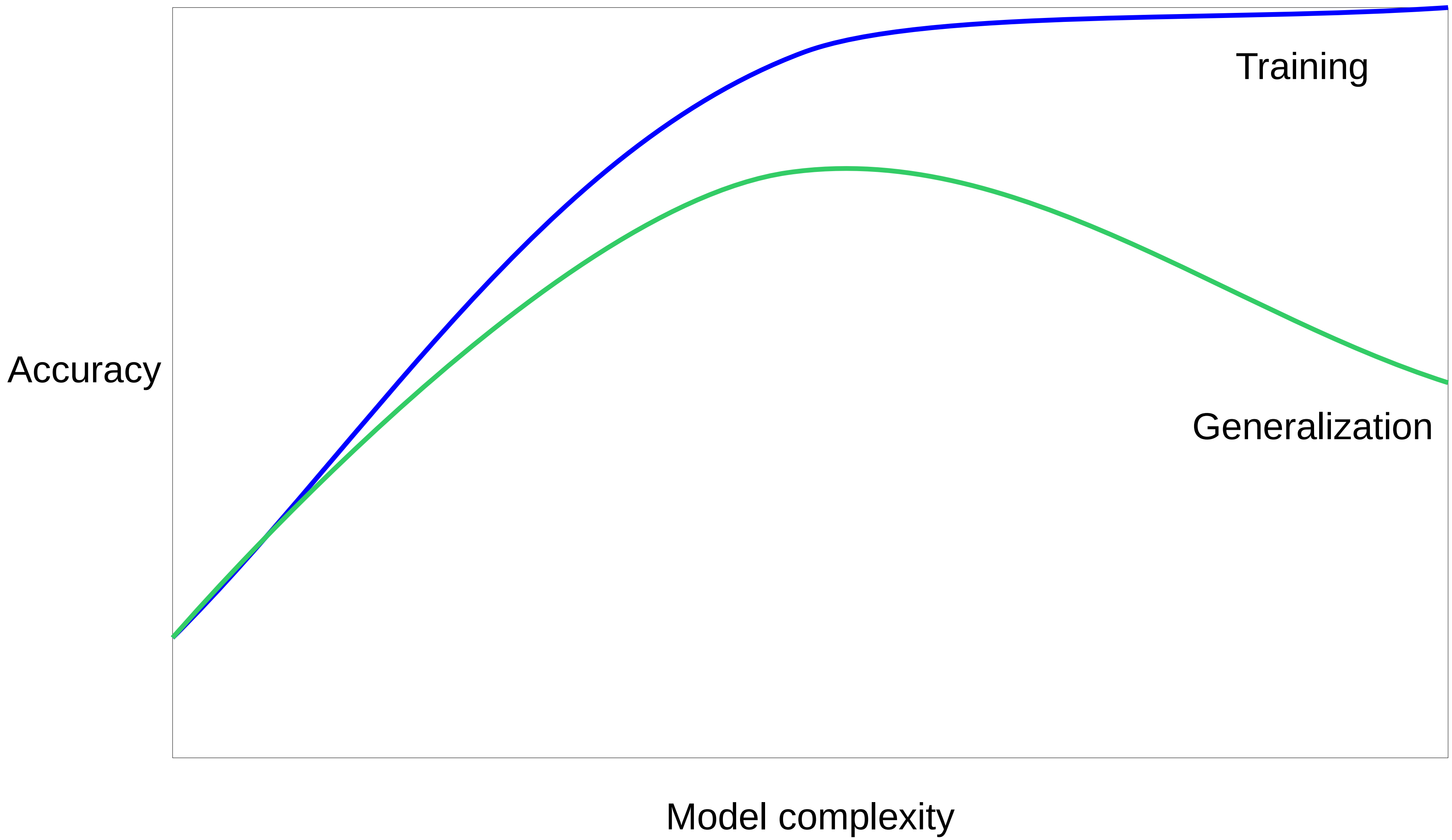
`estimator.predict`	`estimator.transform`
Classification	Preprocessing
Regression	Dimensionality reduction
Clustering	Feature selection
	Feature extraction

Model selection and model complexity (aka bias-variance tradeoff)

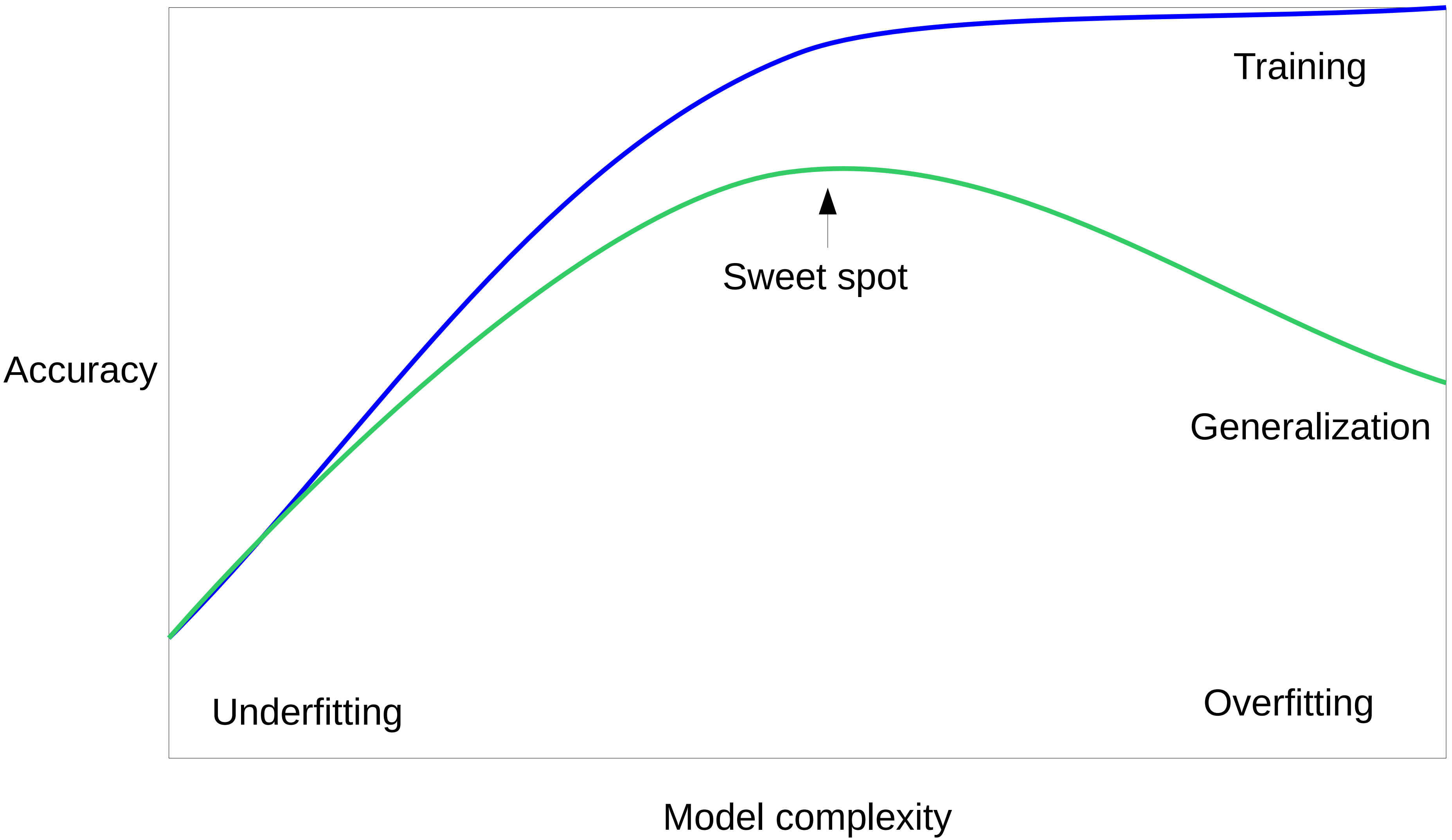
Overfitting and Underfitting



Overfitting and Underfitting



Overfitting and Underfitting



Cross-Validation

```
from sklearn.cross_validation import cross_val_score

scores = cross_val_score(SVC(), X, y, cv=5)
print(scores)

>> [ 0.92  1.    1.    1.    1.  ]
```

Cross-Validation

```
from sklearn.cross_validation import cross_val_score

scores = cross_val_score(SVC(), X, y, cv=5)
print(scores)

>> [ 0.92  1.    1.    1.    1.  ]

cv_ss = ShuffleSplit(len(X_train), test_size=.3,
                     n_iter=10)
scores_shuffle_split = cross_val_score(SVC(), X, y,
                                       cv=cv_ss)
```

Cross-Validation

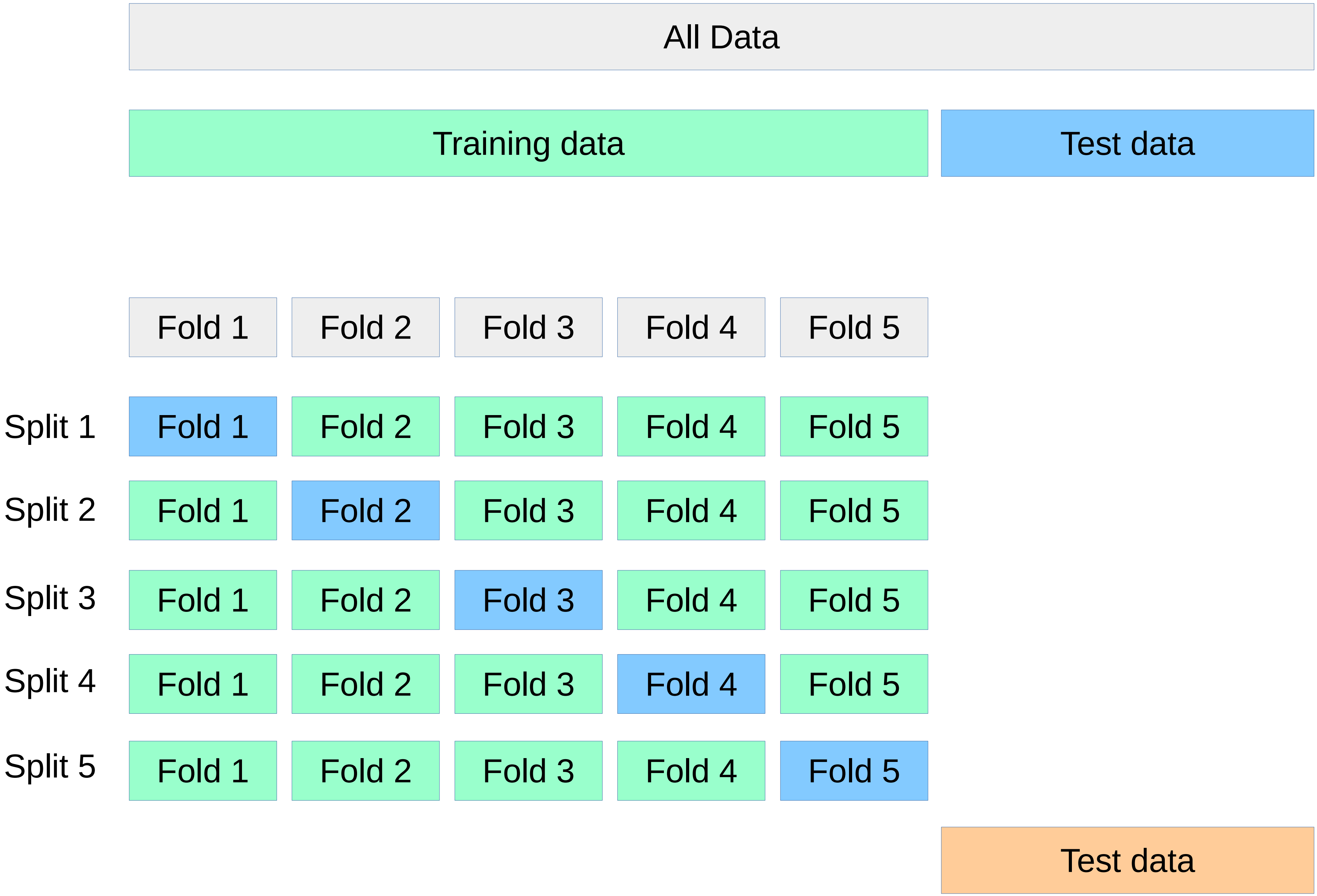
```
from sklearn.cross_validation import cross_val_score

scores = cross_val_score(SVC(), X, y, cv=5)
print(scores)

>> [ 0.92  1.    1.    1.    1.  ]

cv_ss = ShuffleSplit(len(X_train), test_size=.3,
                     n_iter=10)
scores_shuffle_split = cross_val_score(SVC(), X, y,
                                       cv=cv_ss)

cv_labels = LeaveOneLabelOut(labels)
scores_pout = cross_val_score(SVC(), X, y, cv=cv_labels)
```

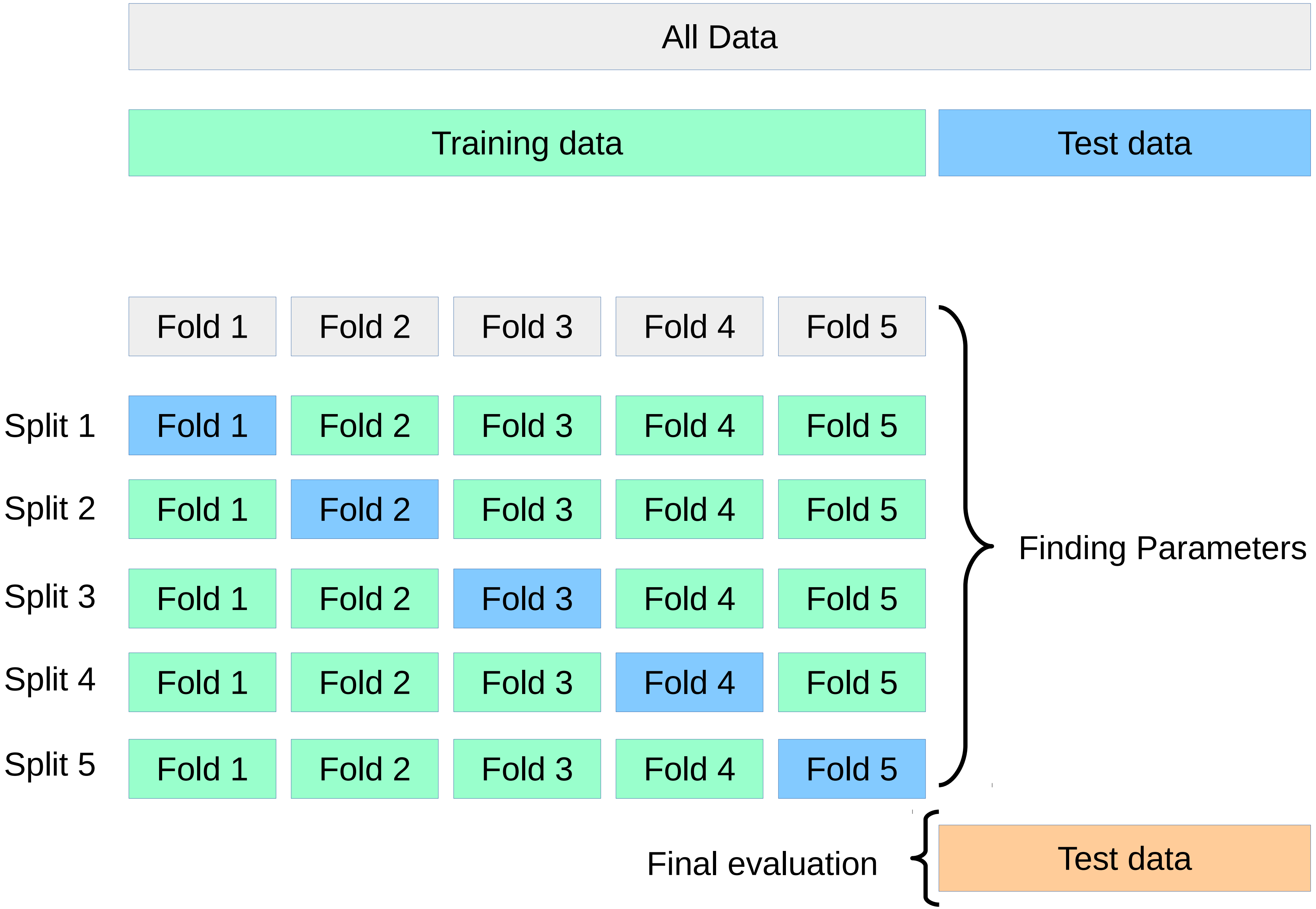
Cross -Validated Grid Search

```
In [2]: clf = SVC()
        clf.fit(X_train, y_train)
```

```
SVC(self, C=1.0, kernel='rbf', degree=3, gamma=0.0, coef0=0.0,
 shrinking=True, probability=False, tol=0.001, cache_size=200,
 class_weight=None, verbose=False, max_iter=-1, random_state=N
one)
```


All Data
Training data
Test data


All Data
Training data
Test data
Fold 1
Fold 2
Fold 3
Fold 4
Fold 5
Split 1
Split 2
Split 3
Split 4
Split 5
Test data


All Data
Training data
Test data
Fold 1
Fold 2
Fold 3
Fold 4
Fold 5
Split 1
Split 2
Split 3
Split 4
Split 5
Finding Parameters
Final evaluation
Test data

Cross -Validated Grid Search

```
from sklearn.grid_search import GridSearchCV
from sklearn.cross_validation import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y)

param_grid = {'C': 10. ** np.arange(-3, 3),
              'gamma': 10. ** np.arange(-3, 3)}
grid = GridSearchCV(SVC(), param_grid=param_grid)
grid.fit(X_train, y_train)
grid.predict(X_test)
grid.score(X_test, y_test)
```

Sample application: Sentiment Analysis

IMDB Movie Reviews Data

Review:
One of the worst movies I've ever rented. Sorry it had one of my favorite actors on it (Travolta) in a nonsense role. In fact, anything made sense in this movie.

Who can say there was true love between Eddy and Maureen? Don't you remember the beginning of the movie ?

Is she so lovely? Ask her daughters. I don't think so.

Label: `negative`

Training data: `12500 positive, 12500 negative`

Bag Of Word Representations

`CountVectorizer` / `TfidfVectorizer`

Bag Of Word Representations

`CountVectorizer` / `TfidfVectorizer`

“This is how you get ants.”

Bag Of Word Representations

`CountVectorizer / TfidfVectorizer`

“This is how you get ants.”

tokenizer

['this', 'is', 'how', 'you', 'get', 'ants']

Bag Of Word Representations

`CountVectorizer / TfidfVectorizer`

```
“This is how you get ants.”
```

tokenizer

```
['this', 'is', 'how', 'you', 'get', 'ants']
```

Build a vocabulary over all documents

```
['aardvak', 'amsterdam', 'ants', ... 'you', 'your', 'zyxst']
```

Bag Of Word Representations

`CountVectorizer` / `TfidfVectorizer`

`“This is how you get ants.”`

tokenizer

`['this', 'is', 'how', 'you', 'get', 'ants']`

Build a vocabulary over all documents

`['aardvak', 'amsterdam', 'ants', ... 'you', 'your', 'zyxst']`

Sparse matrix encoding

aardvak ants get you zyxst
[0, …, 0, 1, 0, … , 0, 1 , 0, …, 0, 1, 0, …., 0]

N-grams (unigrams and bigrams)

`CountVectorizer` / `TfidfVectorizer`

N-grams (unigrams and bigrams)

`CountVectorizer / TfidfVectorizer`

`“This is how you get ants.”`

N-grams (unigrams and bigrams)

`CountVectorizer / TfidfVectorizer`

`“This is how you get ants.”`

Unigram tokenizer

```
['this', 'is', 'how', 'you', 'get', 'ants']
```

N-grams (unigrams and bigrams)

`CountVectorizer / TfidfVectorizer`

`“This is how you get ants.”`

Unigram tokenizer

`['this', 'is', 'how', 'you', 'get', 'ants']`

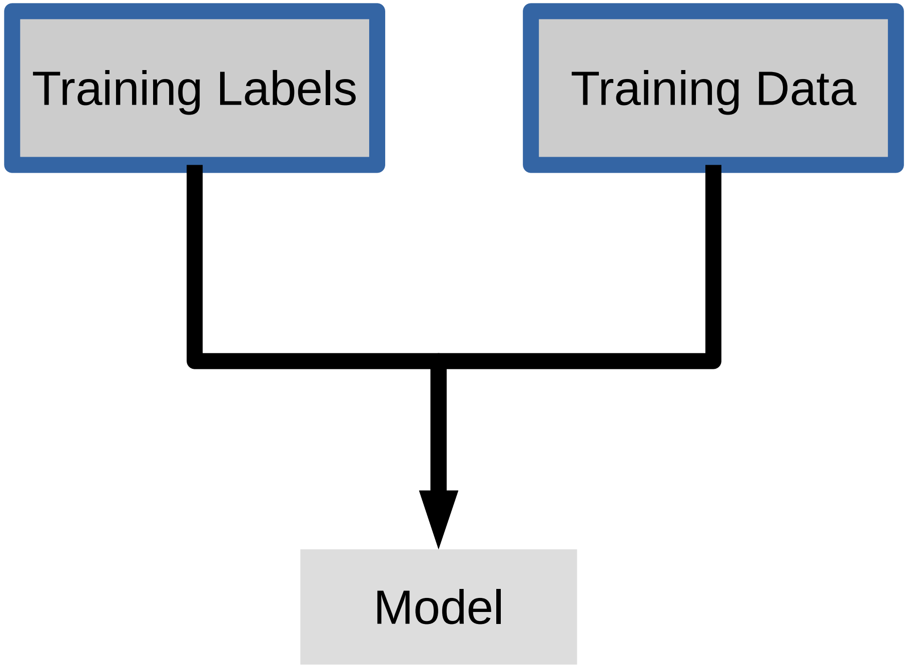
`“This is how you get ants.”`

Bigram tokenizer

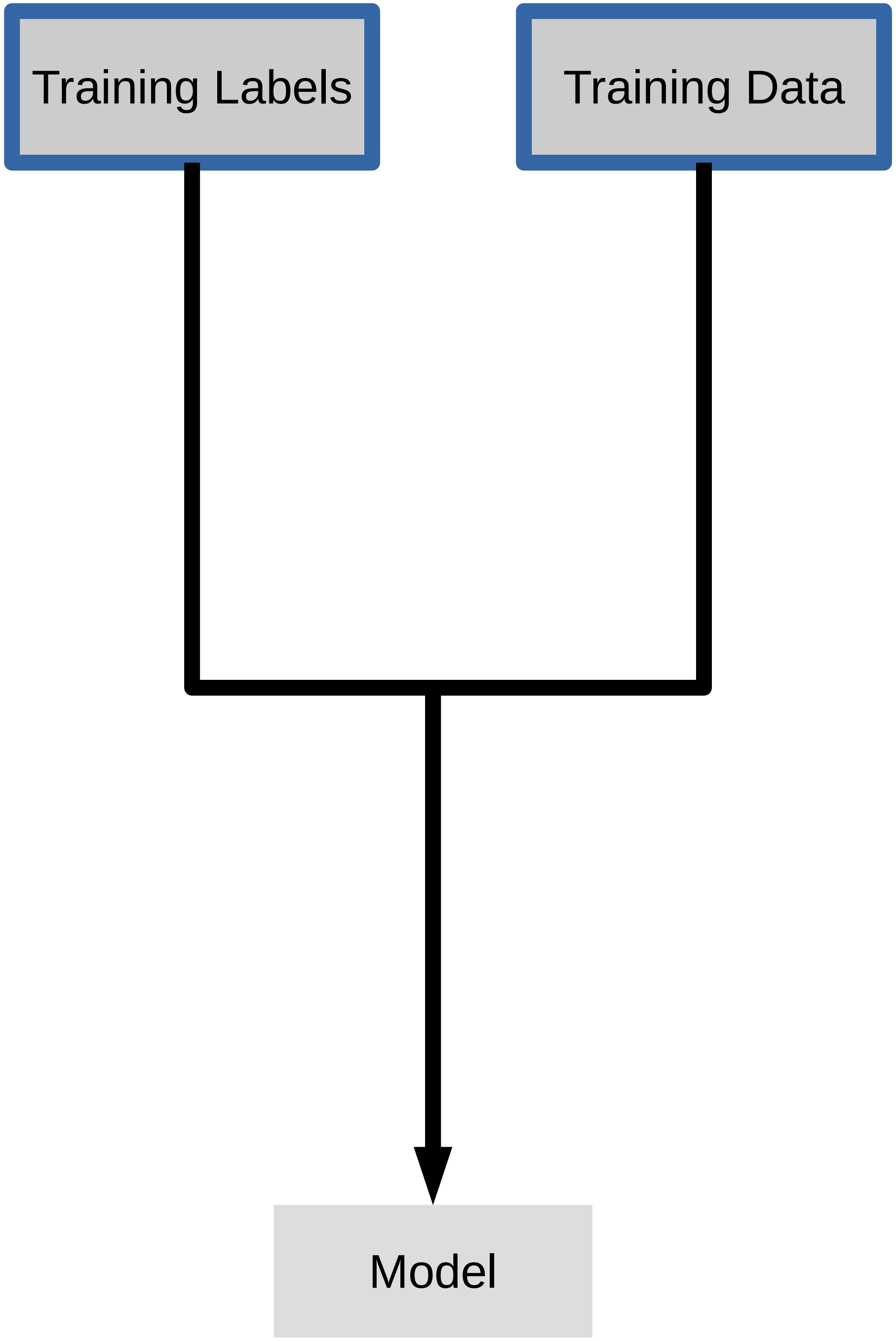
`['this is', 'is how', 'how you', 'you get', 'get ants']`

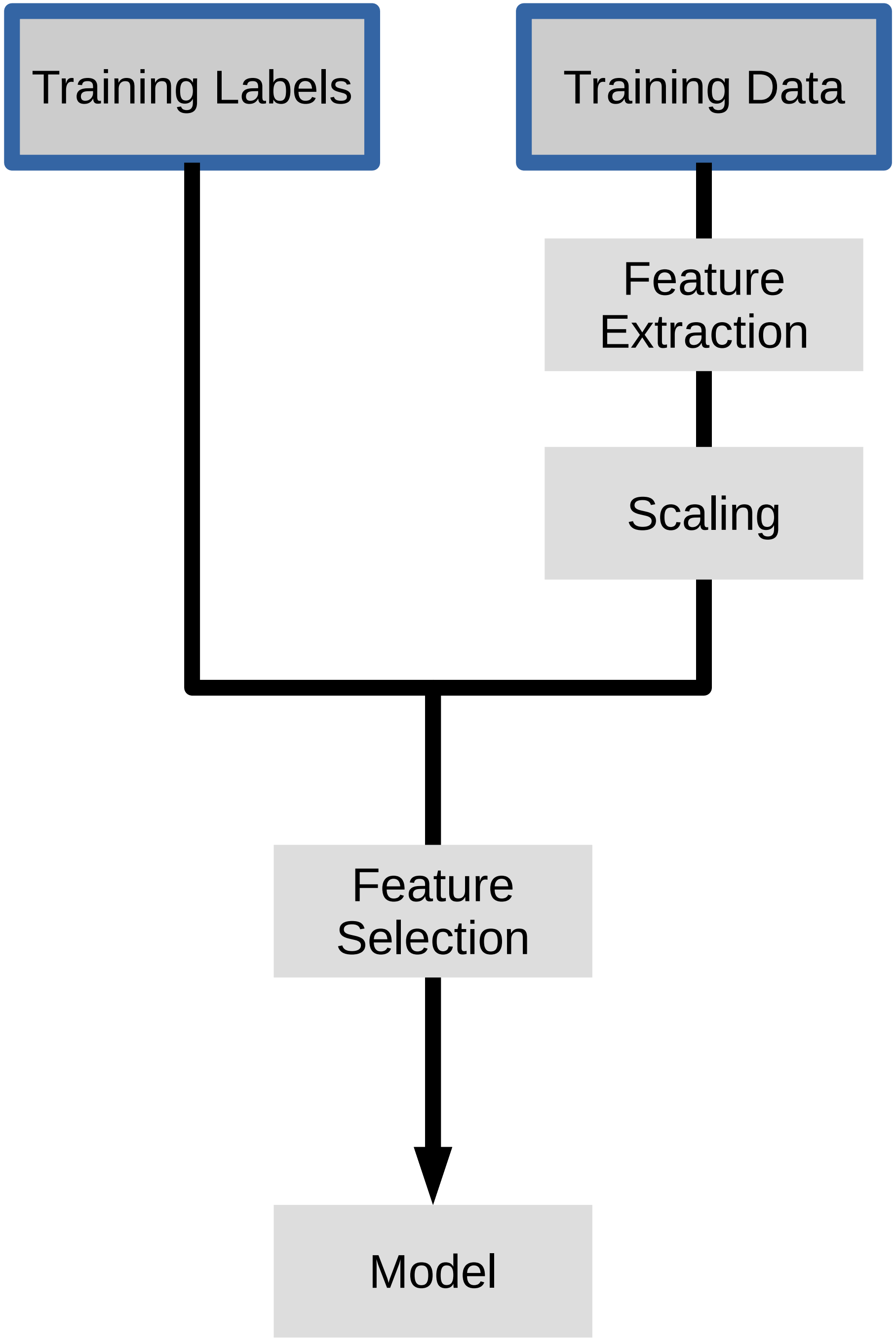
Notebook Working With Text Data

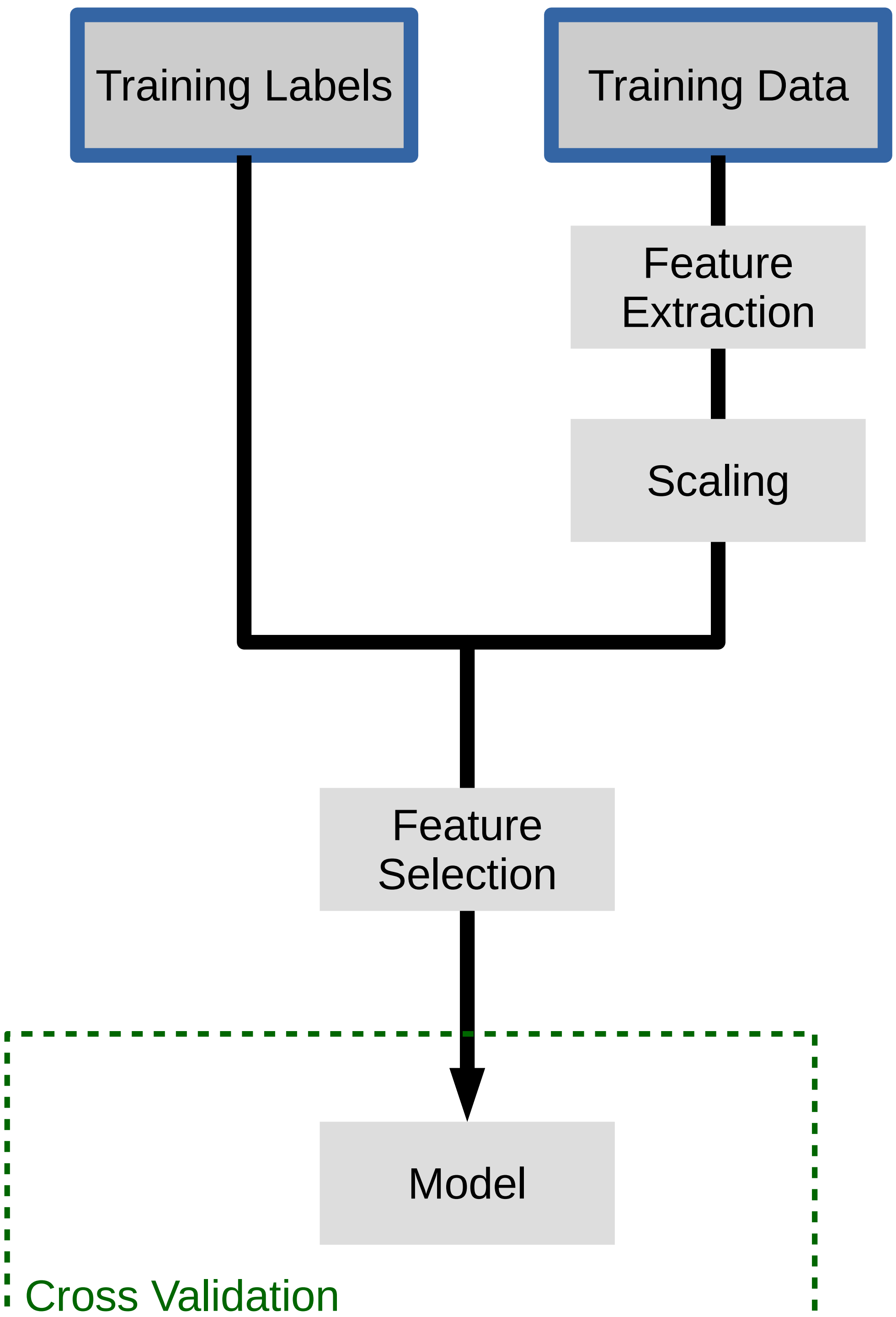
Pipelines

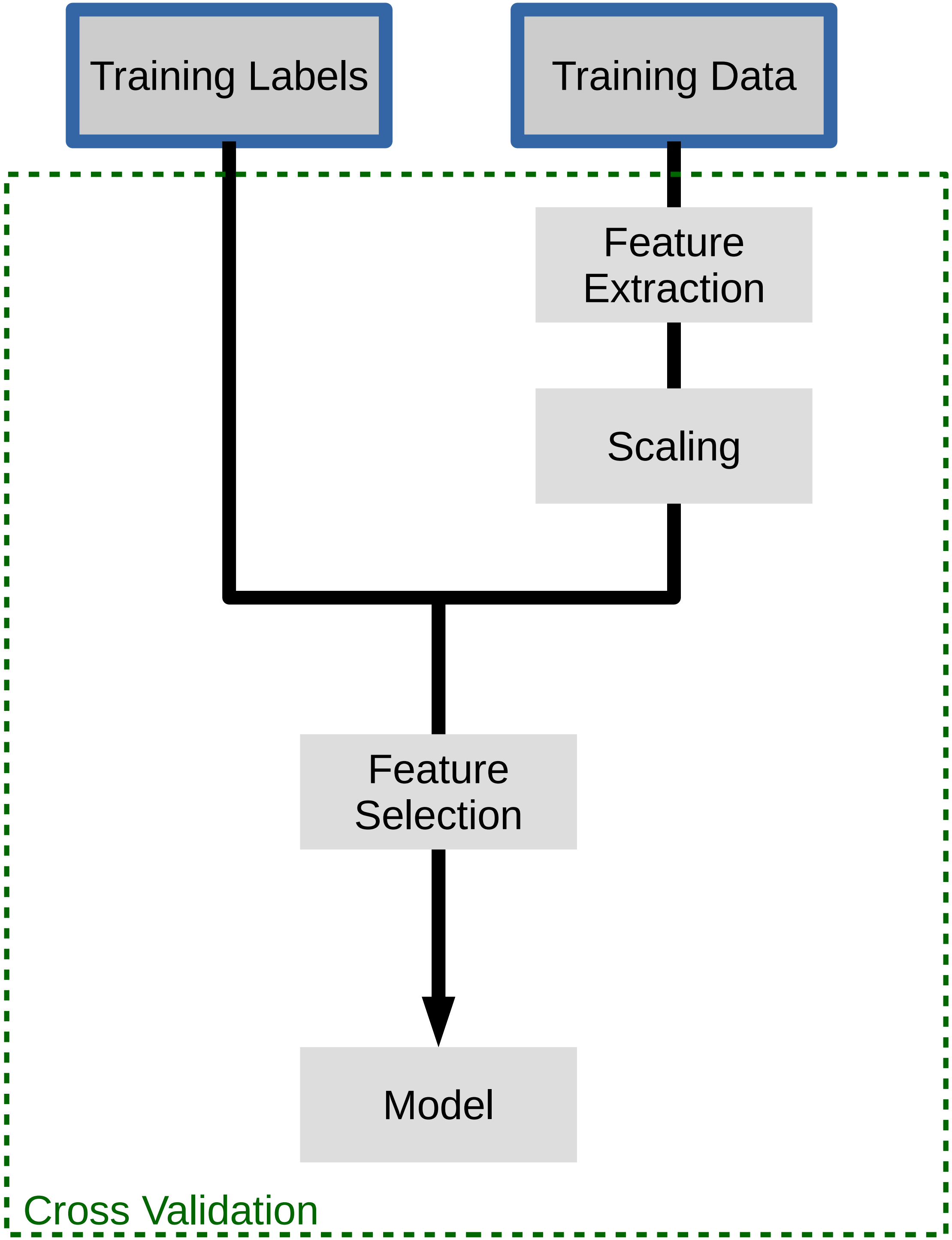


Training Labels
Training Data
Model


Training Labels
Training Data
Model

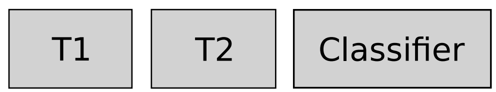

Training Labels
Training Data
Feature Extraction
Scaling
Feature Selection
Model


Training Labels
Training Data
Feature Extraction
Scaling
Feature Selection
Model
Cross Validation

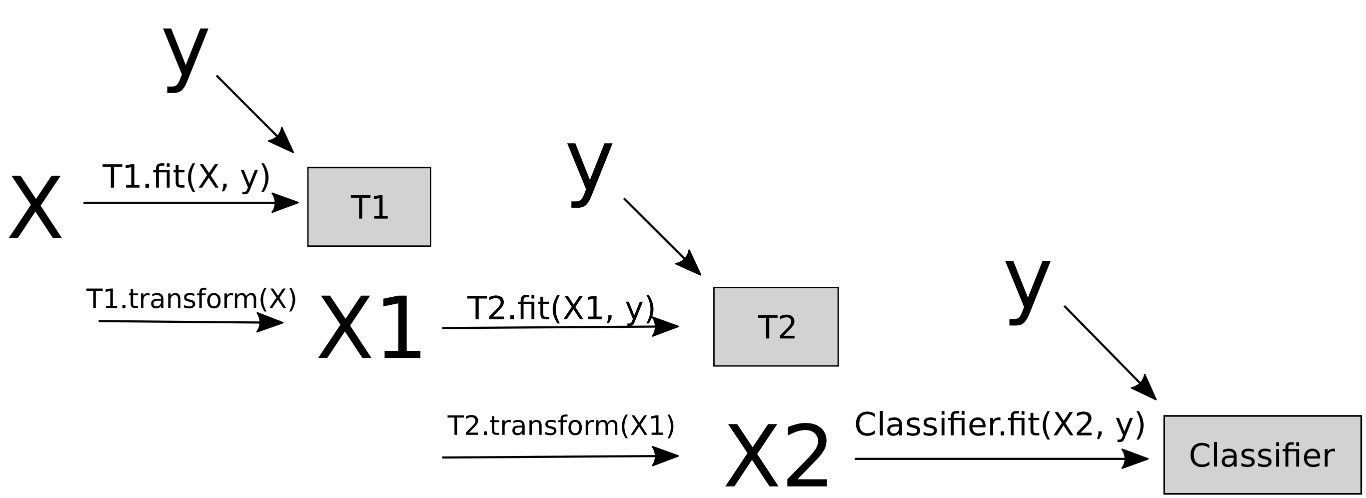

Training Labels
Training Data
Feature Extraction
Scaling
Feature Selection
Model
Cross Validation

Pipelines

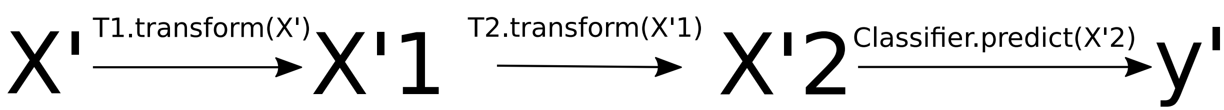
```
pipe = make_pipeline(T1(), T2(), Classifier())
```



pipe.fit(X, y)



pipe.predict(X')



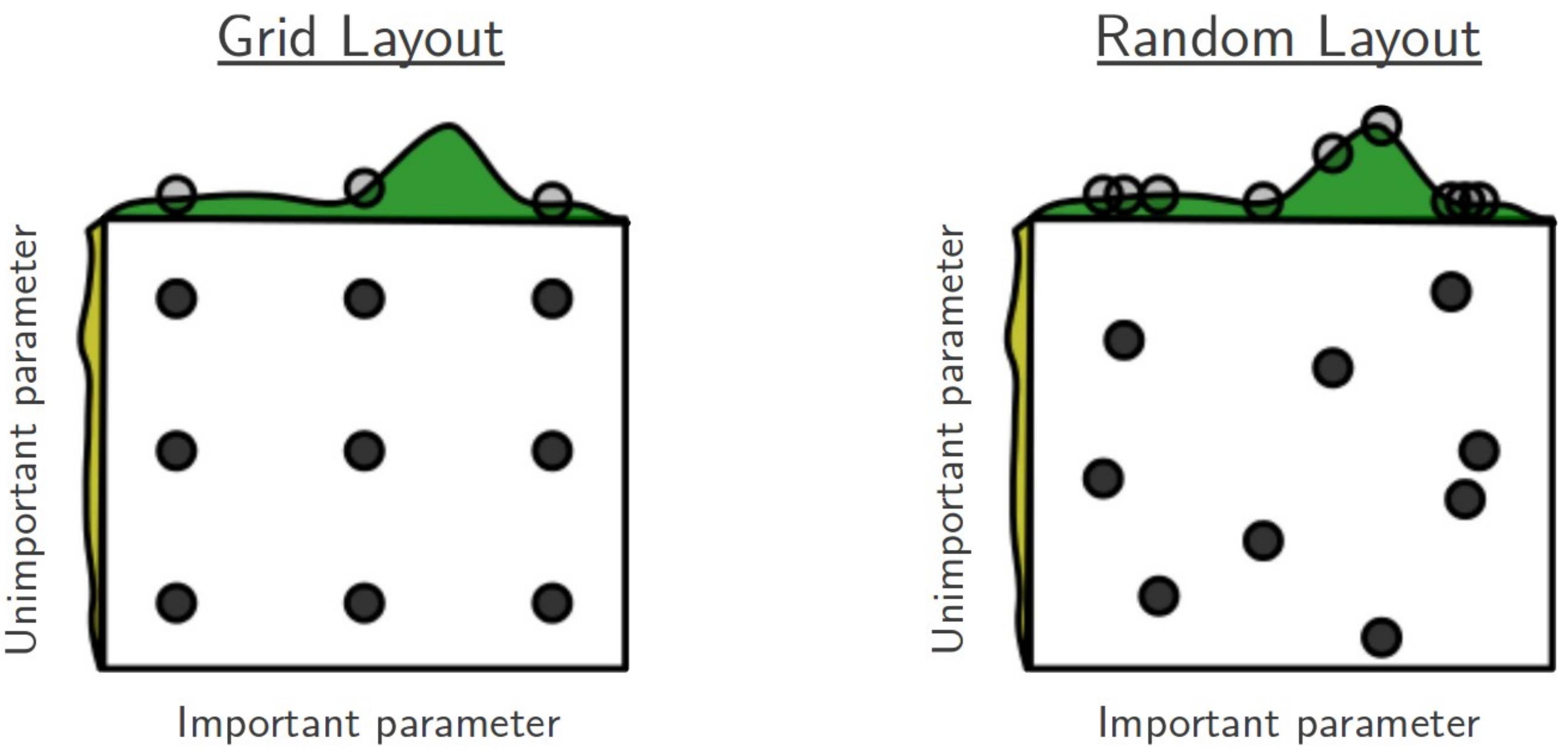
Pipelines

```
from sklearn.pipeline import make_pipeline

pipe = make_pipeline(StandardScaler(), SVC())
pipe.fit(X_train, y_train)
pipe.predict(X_test)
```

Continue Notebook Working with Text Data

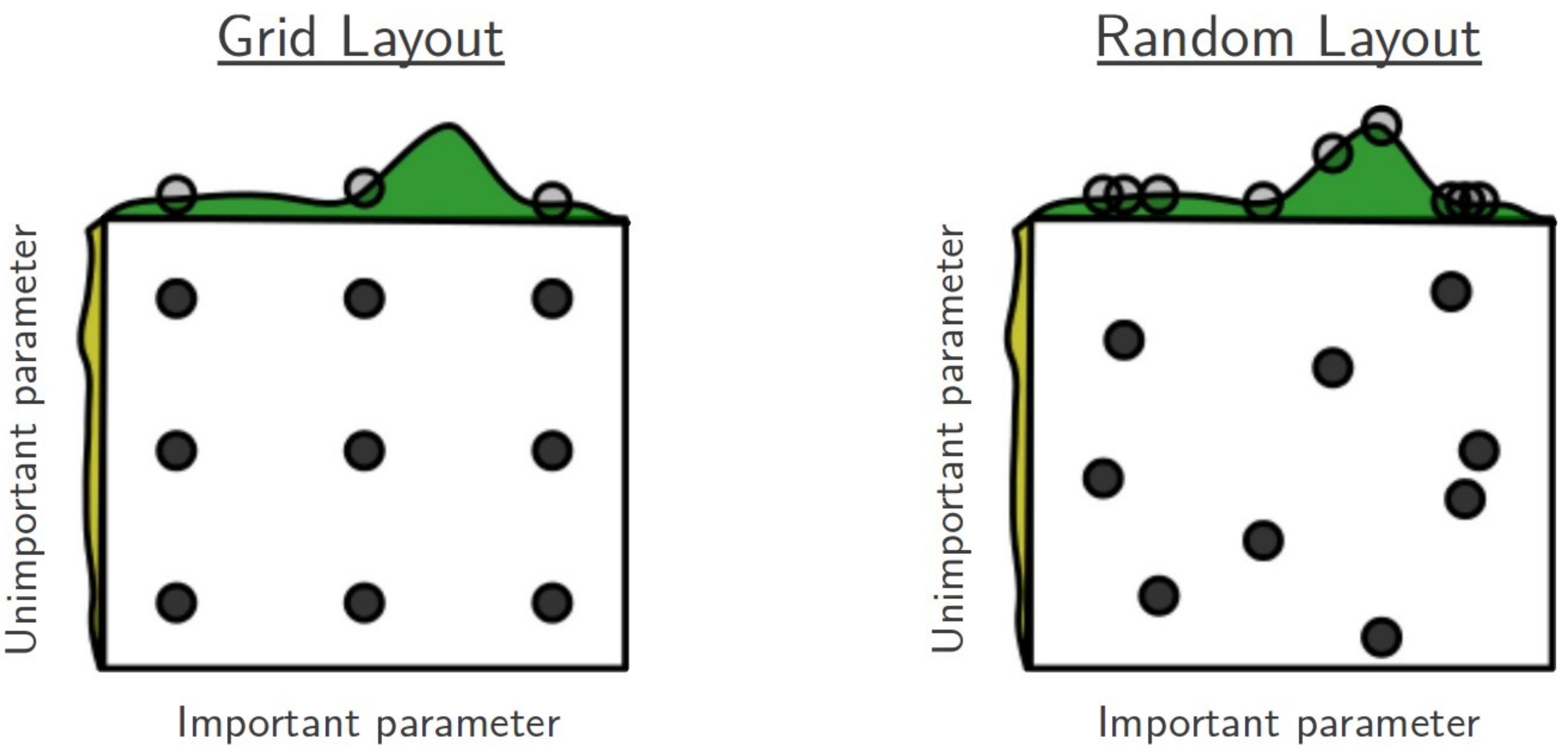
Randomized Parameter Search

Randomized Parameter Search



Source: Bergstra and Bengio

Randomized Parameter Search



Step-size free for continuous parameters
Decouples runtime from search-space size
Robust against irrelevant parameters

Source: Bergstra and Bengio

Randomized Parameter Search

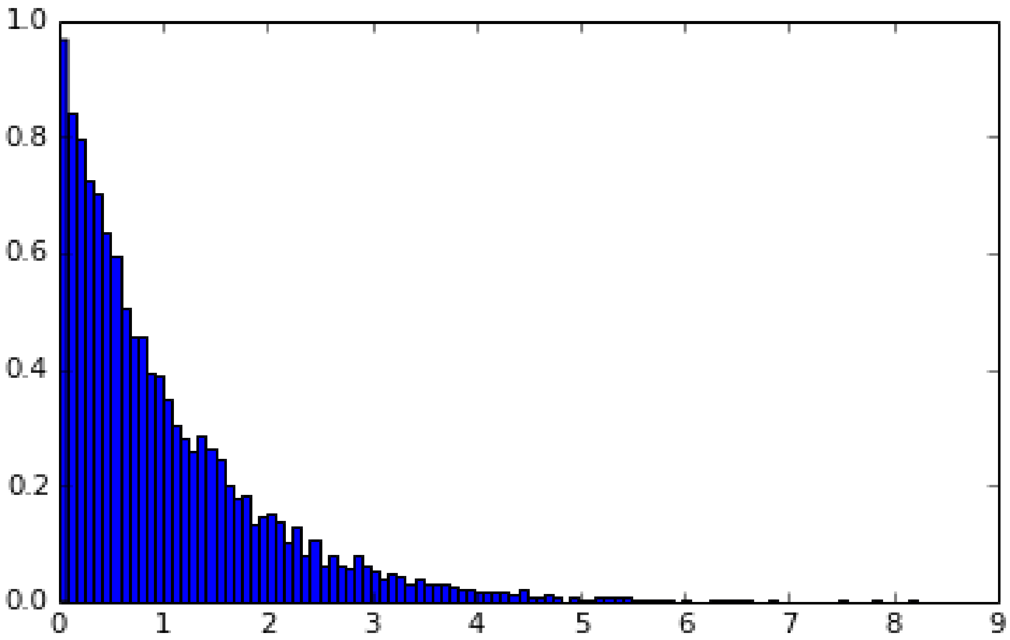
```
params = {'featureunion__countvectorizer-1__ngram_range':
          [(1, 3), (1, 5), (2, 5)],
          'featureunion__countvectorizer-2__ngram_range':
          [(1, 1), (1, 2), (2, 2)],
          'linearsvc__C': 10. ** np.arange(-3, 3)}
```

Randomized Parameter Search

```
params = {'featureunion__countvectorizer-1__ngram_range':
          [(1, 3), (1, 5), (2, 5)],
          'featureunion__countvectorizer-2__ngram_range':
          [(1, 1), (1, 2), (2, 2)],
          'linearsvc__C': expon()}
```

Randomized Parameter Search

```
params = {'featureunion__countvectorizer-1__ngram_range':
          [(1, 3), (1, 5), (2, 5)],
          'featureunion__countvectorizer-2__ngram_range':
          [(1, 1), (1, 2), (2, 2)],
          'linearsvc__C': expon()}
```

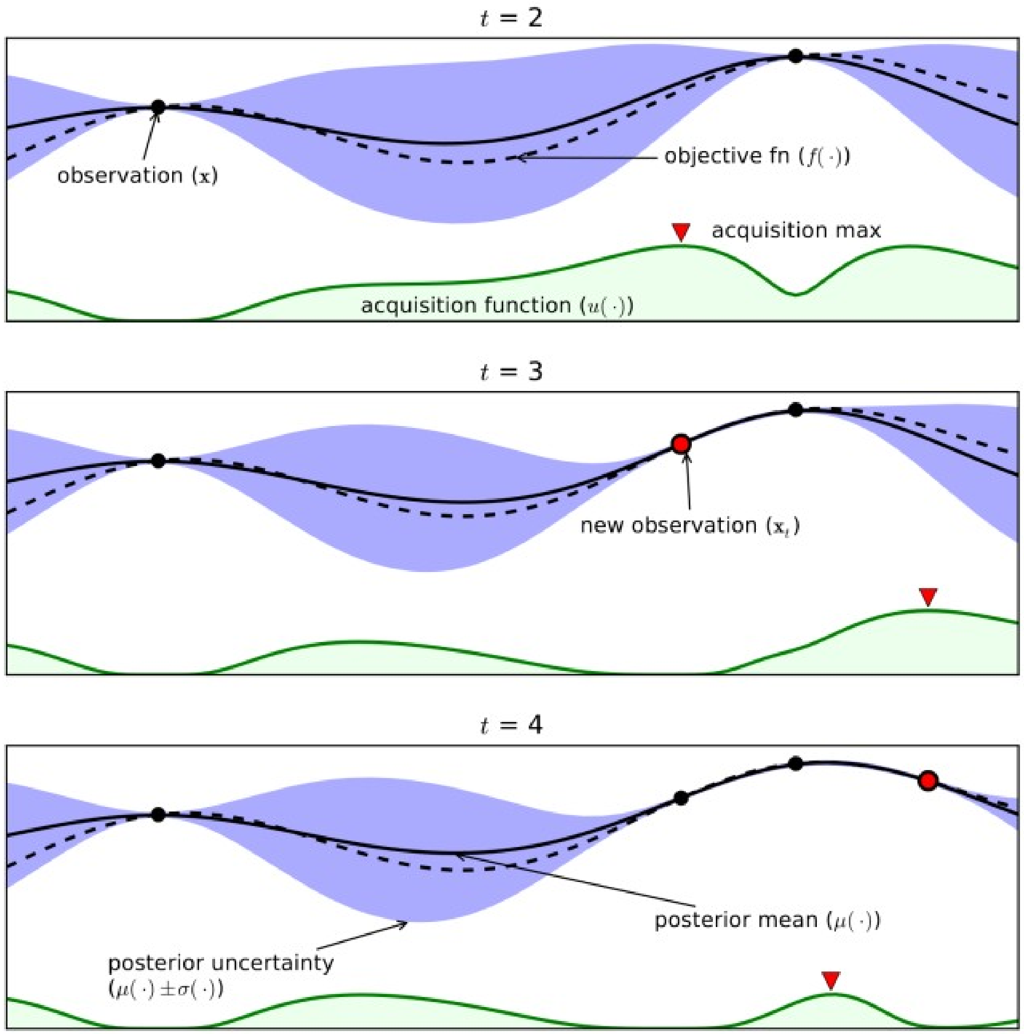



```
rs = RandomizedSearchCV(text_pipe,
    param_distributions=param_distributins, n_iter=50)
```

Randomized Parameter Search

- Always use distributions for continuous variables.
- Don't use for low dimensional spaces.

GP based parameter optimization (coming soon)



From Eric Brochu, Vlad M. Cora and Nando de Freitas

Efficient Parameter Search and Path Algorithms

```
rfe = RFE(LogisticRegression())
```

```python
rfe = RFE(LogisticRegression())
param_grid = {'n_features_to_select': range(1, n_features)}
gridsearch = GridSearchCV(rfe, param_grid)
grid.fit(X, y)
```

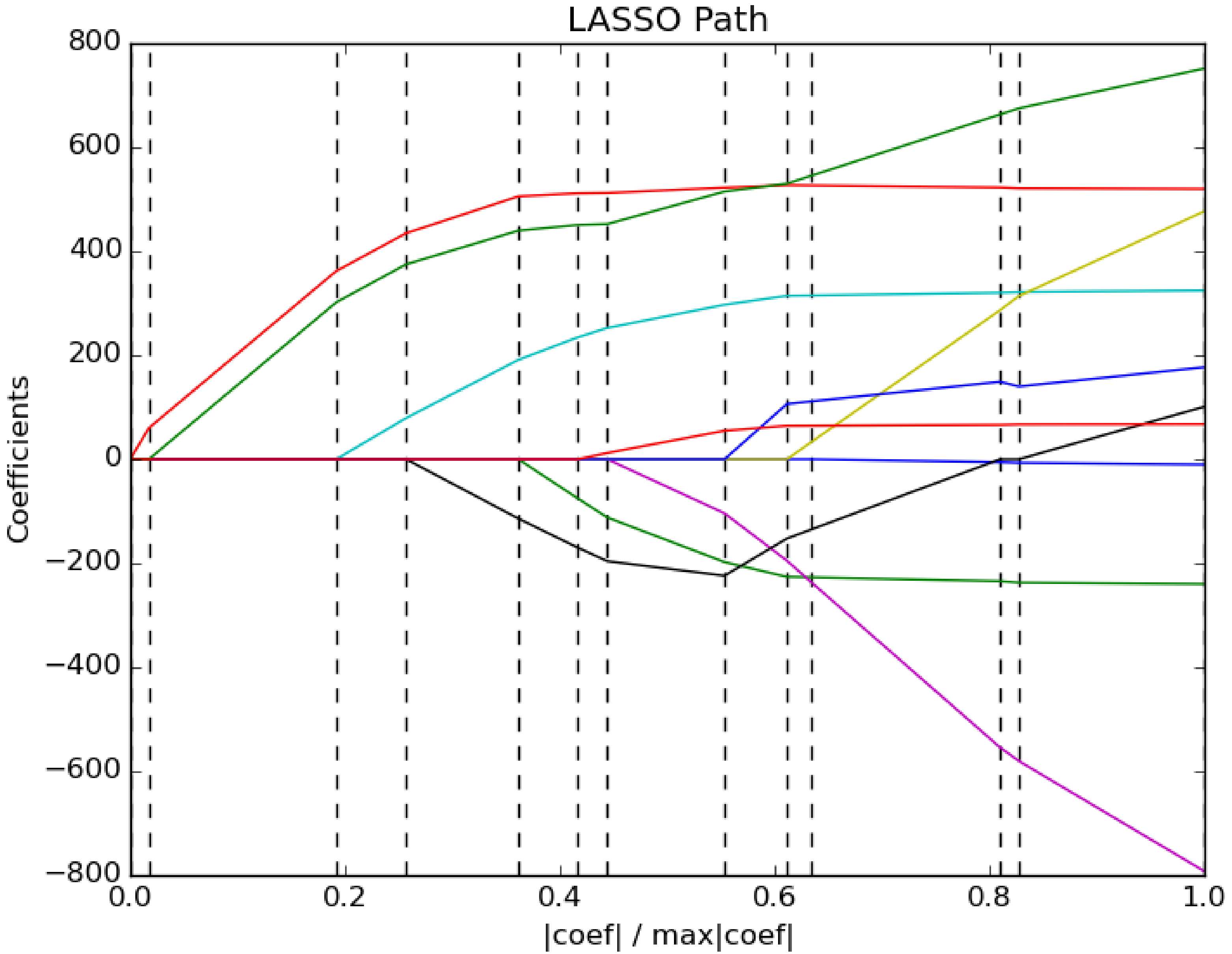
```
rfe = RFE(LogisticRegression())
param_grid = {'n_features_to_select': range(1, n_features)}
gridsearch = GridSearchCV(rfe, param_grid)
grid.fit(X, y)
```

```
rfe = RFE(LogisticRegression())
param_grid = {'n_features_to_select': range(1, n_features)}
gridsearch = GridSearchCV(rfe, param_grid)
grid.fit(X, y)
```

```
rfecv = RFECV(LogisticRegression())
```

```python
rfe = RFE(LogisticRegression())
param_grid = {'n_features_to_select': range(1, n_features)}
gridsearch = GridSearchCV(rfe, param_grid)
grid.fit(X, y)
```

```python
rfecv = RFECV(LogisticRegression())
rfecv.fit(X, y)
```



LASSO Path
800
600
400
200
0
−200
−400
−600
−800
Coefficients
0.0
0.2
0.4
0.6
0.8
1.0
|coef| / max|coef|

Linear Models	Feature Selection	Tree-Based models [possible]
`LogisticRegressionCV [new]`	`RFECV`	`[DecisionTreeCV]`
`RidgeCV`		`[RandomForestClassifierCV]`
`RidgeClassifierCV`		`[GradientBoostingClassifierCV]`
`LarsCV`		
`ElasticNetCV` `...`		

Notebook Efficient Parameter Search

Scoring Functions

GridSeachCV
RandomizedSearchCV
cross_val_score
...CV

Default:
Accuracy (classification)
R2 (regression)

Notebook scoring metrics

Out of Core Learning

- Large Scale – “Out of core: Fits on a hard disk but in RAM”

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- Non-linear – because real-world problems are not.

- Large Scale – “Out of core: Fits on a hard disk but in RAM”

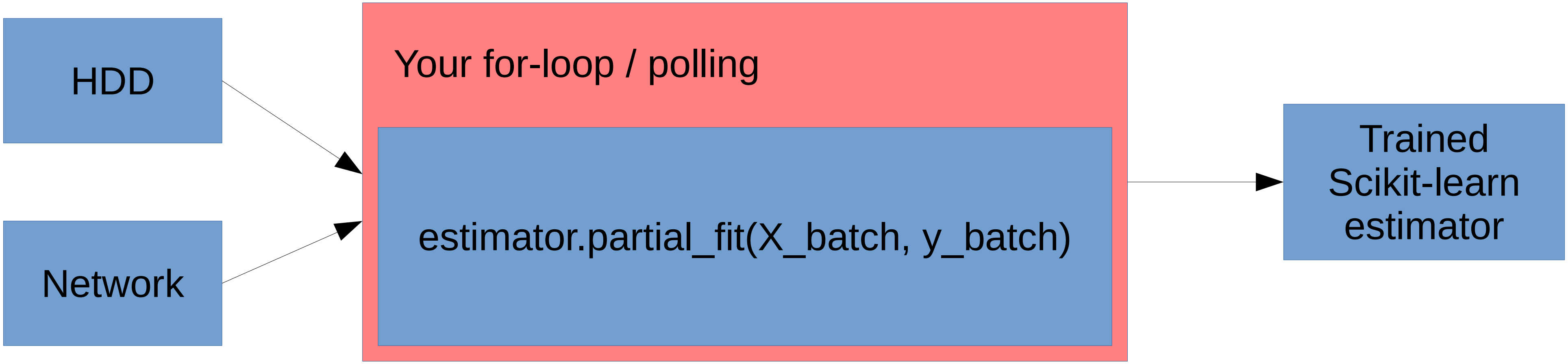
- Non-linear – because real-world problems are not.

- Single CPU – Because parallelization is hard (and often unnecessary)

Think twice!

- Old laptop: 4GB Ram
- 1073741824 float32
- Or 1mio data points with 1000 features
- EC2 : 256 GB Ram
- 68719476736 float32
- Or 68mio data points with 1000 features

	vCPU	ECU	Memory (GiB)	Instance Storage (GB)	Linux/UNIX Usage
Memory Optimized - Current Generation					
r3.large	2	6.5	15	1 x 32 SSD	$0.195 per Hour
r3.xlarge	4	13	30.5	1 x 80 SSD	$0.39 per Hour
r3.2xlarge	8	26	61	1 x 160 SSD	$0.78 per Hour
r3.4xlarge	16	52	122	1 x 320 SSD	$1.56 per Hour
r3.8xlarge	32	104	244	2 x 320 SSD	$3.12 per Hour
Storage Optimized - Current Generation					
i2.xlarge	4	14	30.5	1 x 800 SSD	$0.938 per Hour
i2.2xlarge	8	27	61	2 x 800 SSD	$1.876 per Hour
i2.4xlarge	16	53	122	4 x 800 SSD	$3.751 per Hour
i2.8xlarge	32	104	244	8 x 800 SSD	$7.502 per Hour


HDD
Network
Your for-loop / polling
estimator.partial_fit(X_batch, y_batch)
Trained
Scikit-learn
estimator

Supported Algorithms

- All `SGDClassifier` derivatives
- Naive Bayes
- `MinibatchKMeans`
- `IncrementalPCA`
- `MiniBatchDictionaryLearning`
- `MultilayerPerceptron (dev branch)`
- `Scalers`

Out of Core Learning

```
sgd = SGDClassifier()

for i in range(9):
    X_batch, y_batch = cPickle.load(open("batch_%02d" % i))
    sgd.partial_fit(X_batch, y_batch, classes=range(10))
```

Possibly go over the data multiple times.

The hashing trick for text data

Text Classification: Bag Of Word

```
“This is how you get ants.”
```

tokenizer

```
['this', 'is', 'how', 'you', 'get', 'ants']
```

Build a vocabulary over all documents

```
['aardvak', 'amsterdam', 'ants', ... 'you',
'your', 'zyxst']
```

Sparse matrix encoding

aardvak ants get you zyxst
[0, …, 0, 1, 0, … , 0, 1 , 0, …, 0, 1, 0, …., 0]

Text Classification: Hashing Trick

“This is how you get ants.”

tokenizer

```
['this', 'is', 'how', 'you', 'get', 'ants']
```

hashing

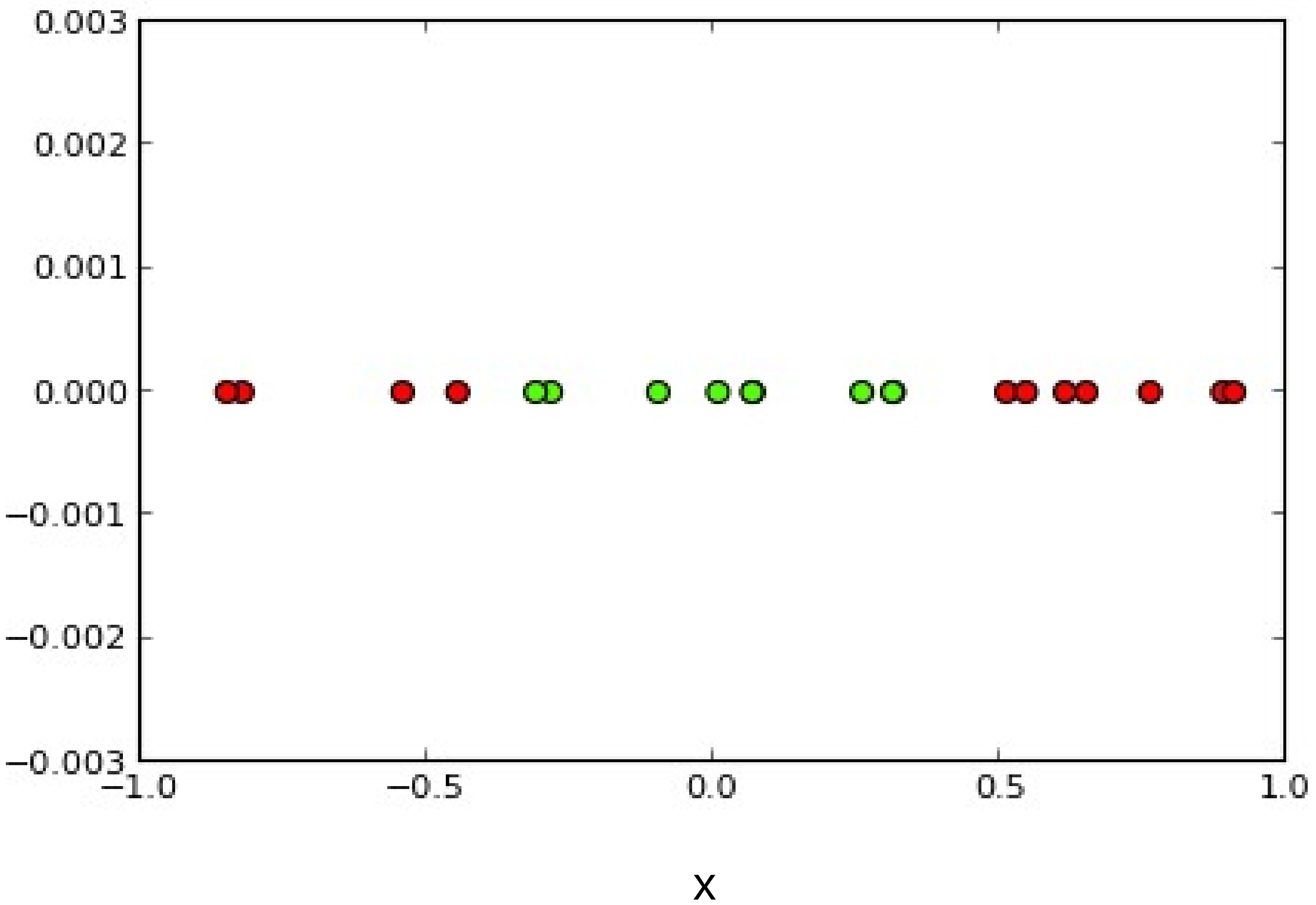
```
[hash('this'), hash('is'), hash('how'), hash('you'),
hash('get'), hash('ants')]
= [832412, 223788, 366226,  81185, 835749, 173092]
```

Sparse matrix encoding

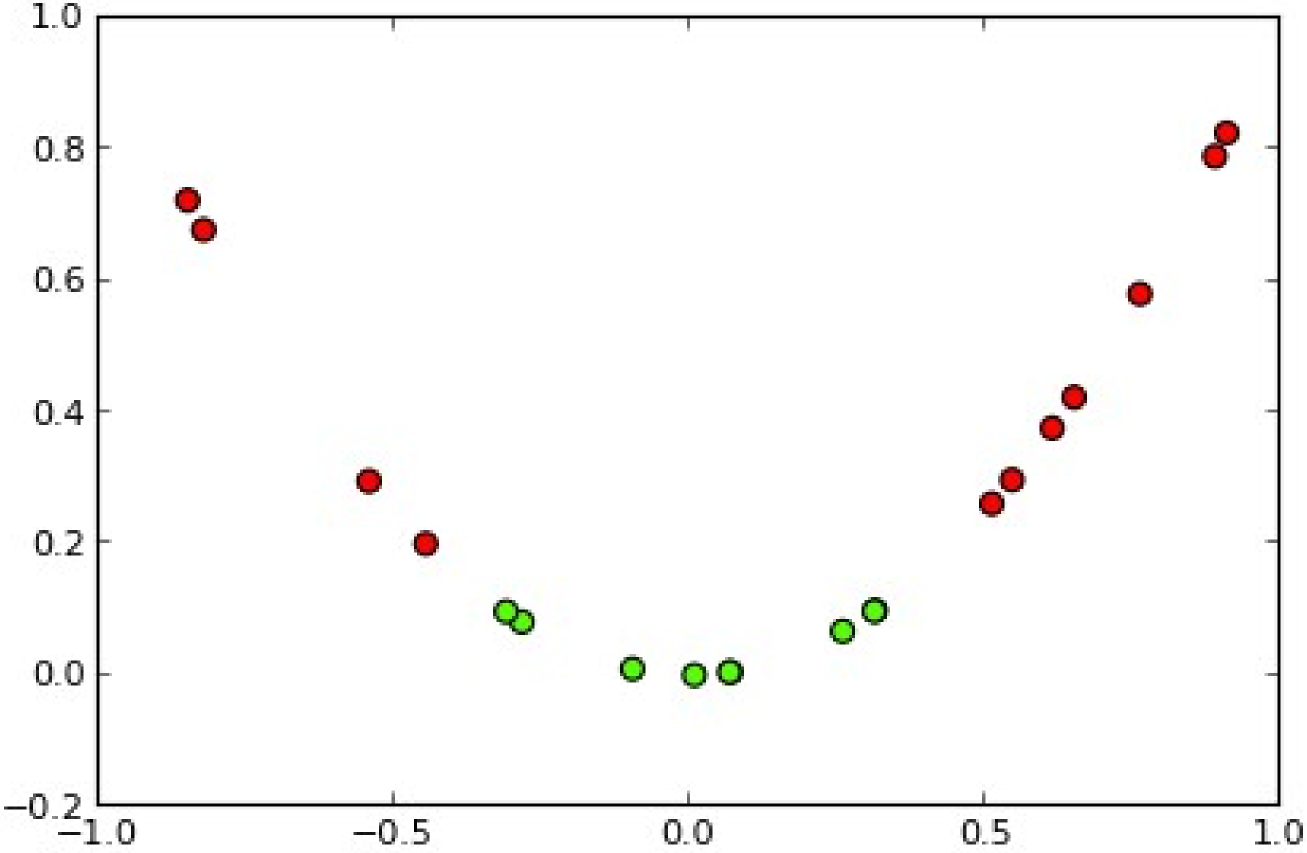
[0, …, 0, 1, 0, … , 0, 1 , 0, …, 0, 1, 0, …., 0]

Kernel Approximations

Reminder: Kernel Trick



Reminder: Kernel Trick



$\phi(x)$

Reminder: Kernel Trick

Classifier linear → need only

$$\langle \phi(x_i), \phi(x_j) \rangle = k(x_i, x_j)$$

Reminder: Kernel Trick

Classifier linear → need only

$$\langle \phi(x_i), \phi(x_j) \rangle = k(x_i, x_j)$$

Linear: $\langle x, x' \rangle$

Polynomial: $(\gamma \langle x, x' \rangle + r)^d$

RBF: $\exp(-\gamma |x - x'|^2)$

Sigmoid: $\tanh(\gamma \langle x, x' \rangle + r)$

Complexity

- Solving kernelized SVM:
  ~O(n_samples ** 3)
- Solving linear (primal) SVM:
  ~O(n_samples * n_features)

n_samples large? Go primal!

Undoing the Kernel Trick

- Kernel approximation:

$$\langle\hat{\phi}(x_i), \hat{\phi}(x_j)\rangle \approx k(x_i, x_j)$$

- k = $\exp(-\gamma|x - x'|^2)$
  $\hat{\phi}$ = RBFSampler

Usage

```
sgd = SGDClassifier()
kernel_approximation = RBFSampler(gamma=.001, n_components=400)

for i in range(9):
    X_batch, y_batch = cPickle.load(open("batch_%02d" % i))
    if i == 0:
        kernel_approximation.fit(X_batch)
    X_transformed = kernel_approximation.transform(X_batch)
    sgd.partial_fit(X_transformed, y_batch, classes=range(10))
```

How (and why) to build your own estimator

Why?

GridSearchCV
cross_val_score
Pipeline

How

- “fit” method
- set_params and get_params (or inherit)
- Run check_estimator

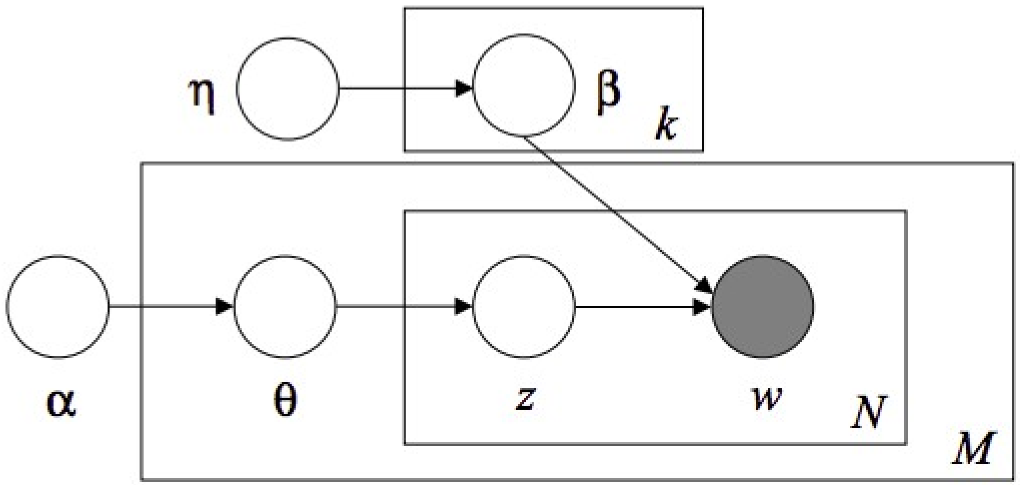
See the “build your own estimator” docs!

Notebook Building your own estimator

What's new in 0.17

Latent Dirichlet Allocation

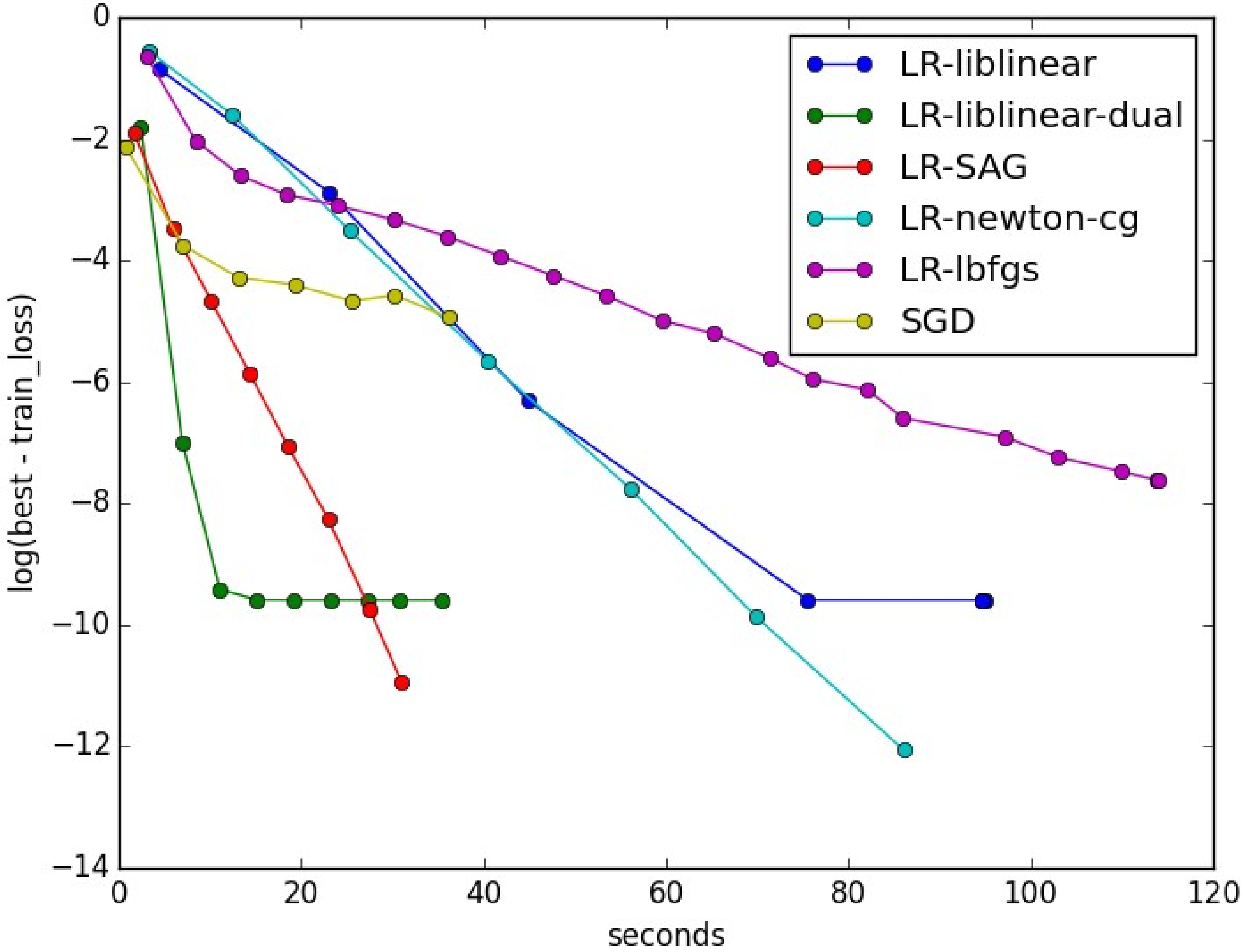
using online variational inference



Topic #0:
government people mr law gun state president states public use right rights national new control american security encryption health united
Topic #1:
drive card disk bit scsi use mac memory thanks pc does video hard speed apple problem used data monitor software
Topic #2:
said people armenian armenians turkish did saw went came women killed children turkey told dead didn left started greek war
Topic #3:
year good just time game car team years like think don got new play games ago did season better ll
Topic #4:
10 00 15 25 12 11 20 14 17 16 db 13 18 24 30 19 27 50 21 40
Topic #5:
windows window program version file dos use files available display server using application set edu motif package code ms software
Topic #6:
edu file space com information mail data send available program ftp email entry info list output nasa address anonymous internet
Topic #7:
ax max b8f g9v a86 pl 145 1d9 0t 34u 1t 3t giz bhj wm 2di 75u 2tm bxn 7ey
Topic #8:
god people jesus believe does say think israel christian true life jews did bible don just know world way church
Topic #9:
don know like just think ve want does use good people key time way make problem really work say need

By Chyi-Kwei Yau, based on code by Matt Hoffman

SAG for Logistic Regression and Ridge Regression



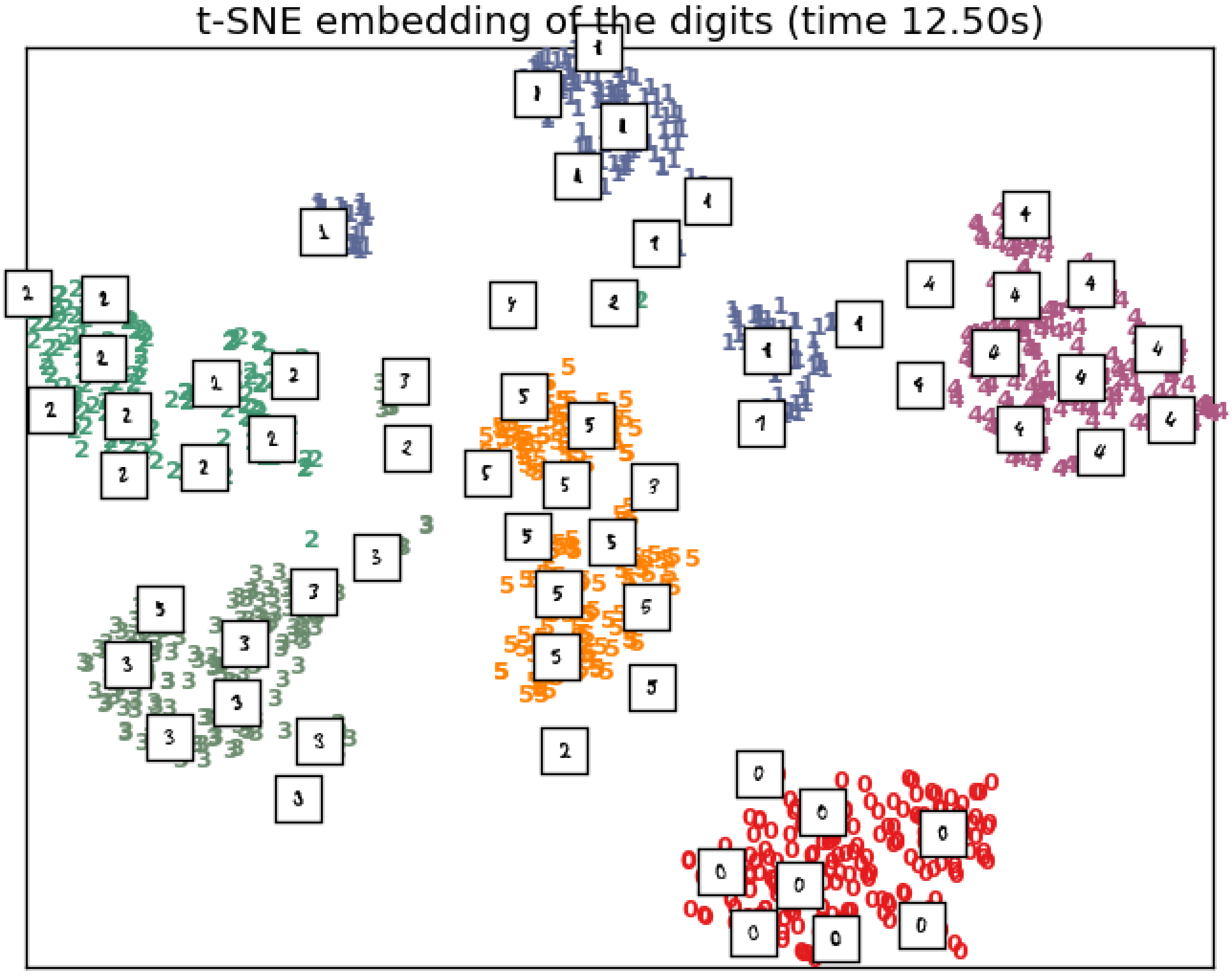
By Danny Sullivan and Tom Dupre la Tour

Coordinate Descent Solver for Non-Negative Matrix Factorization

Topics in NMF model:
Topic #0:
don people just like think know time good right ve make say want did really way new use going said
Topic #1:
windows file dos files window program use running using version ms problem server pc screen ftp run application os software
Topic #2:
god jesus bible christ faith believe christians christian heaven sin hell life church truth lord say belief does existence man
Topic #3:
geb dsl n3jxp chastity cadre shameful pitt intellect skepticism surrender gordon banks soon edu lyme blood weight patients medical probably
Topic #4:
key chip encryption clipper keys escrow government algorithm secure security encrypted public des nsa enforcement bit privacy law secret use
Topic #5:
drive scsi ide drives disk hard controller floppy hd cd mac boot rom cable internal tape bus seagate bios quantum
Topic #6:
game team games players year hockey season play win league teams nhl baseball player detroit toronto runs pitching best playoffs
Topic #7:
thanks mail does know advance hi info looking anybody address appreciated help email information send ftp post interested list appreciate
Topic #8:
card video monitor vga bus drivers cards color driver ram ati mode memory isa graphics vesa pc vlb diamond bit
Topic #9:
00 sale 50 shipping 20 10 price 15 new 25 30 dos offer condition 40 cover asking 75 interested 01

By Tom Dupre la Tour and Mathieu Blondel

Barnes-Hut Approximation for T-SNE manifold learning



FunctionTransformer

```
>>> import numpy as np
>>> from sklearn.preprocessing import FunctionTransformer
>>> transformer = FunctionTransformer(np.log1p)
>>> X = np.array([[0, 1], [2, 3]])
>>> transformer.transform(X)
array([[ 0.        ,  0.69314718],
       [ 1.09861229,  1.38629436]])
```

VotingClassifier

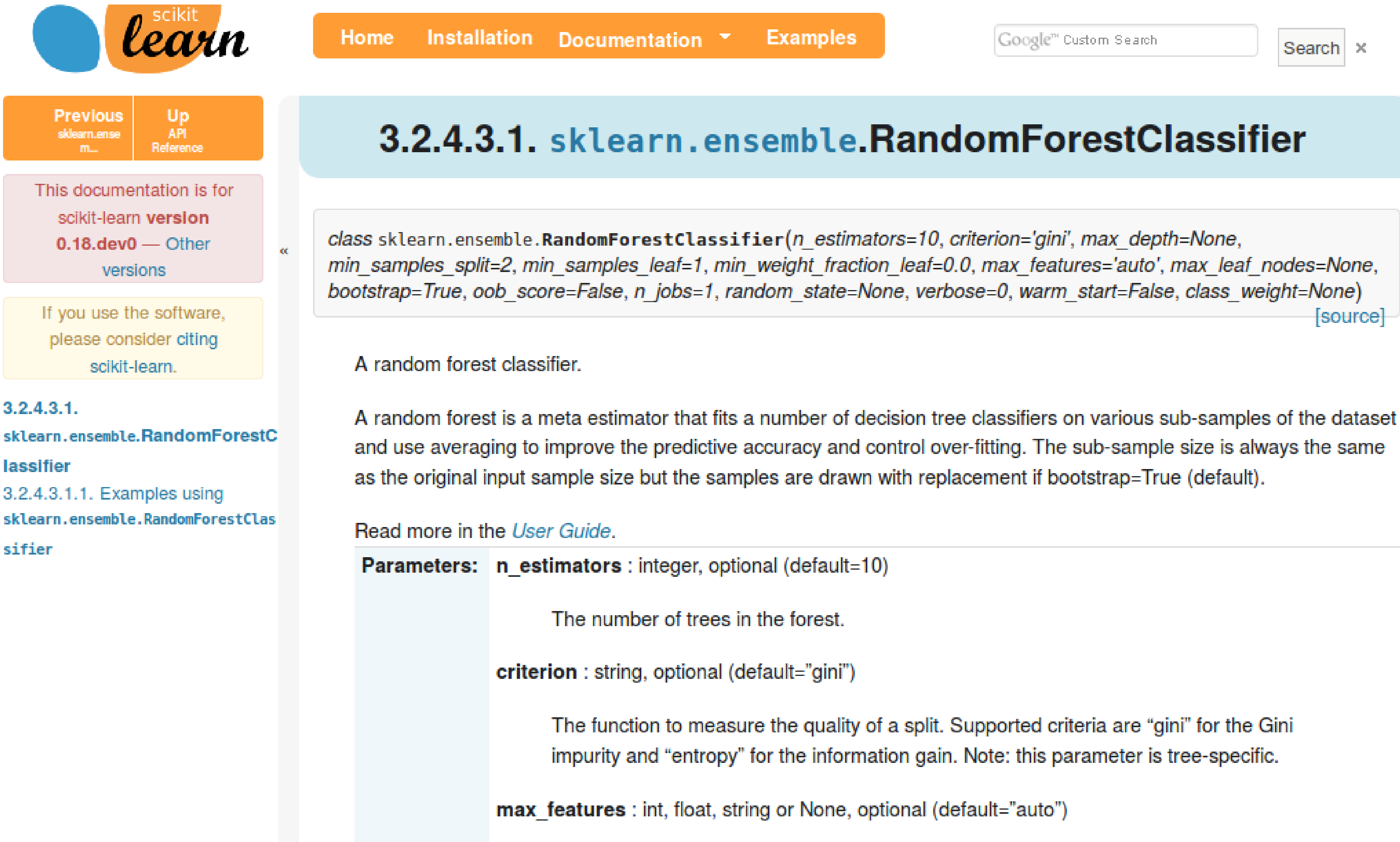
```
clf1 = LogisticRegression()
clf2 = RandomForestClassifier()
clf3 = GaussianNB()

eclf = VotingClassifier(
    estimators=[('lr', clf1), ('rf', clf2), ('gbn', clf3)],
   voting=”hard”)
```

Scalers

- `RobustScaler`
- `MaxAbsScaler`

By Thomas Unterthiner.

Add Backlinks to Docs



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This documentation is for scikit-learn **version 0.18.dev0** — Other versions

If you use the software, please consider citing scikit-learn.

3.2.4.3.1. `sklearn.ensemble.RandomForestClassifier`

3.2.4.3.1.1. Examples using `sklearn.ensemble.RandomForestClassifier`

3.2.4.3.1. `sklearn.ensemble`.RandomForestClassifier

class `sklearn.ensemble.`**`RandomForestClassifier`**(*n_estimators=10, criterion='gini', max_depth=None, min_samples_split=2, min_samples_leaf=1, min_weight_fraction_leaf=0.0, max_features='auto', max_leaf_nodes=None, bootstrap=True, oob_score=False, n_jobs=1, random_state=None, verbose=0, warm_start=False, class_weight=None*) [source]

A random forest classifier.

A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and use averaging to improve the predictive accuracy and control over-fitting. The sub-sample size is always the same as the original input sample size but the samples are drawn with replacement if bootstrap=True (default).

Read more in the *User Guide*.

Parameters:

n_estimators : integer, optional (default=10)

The number of trees in the forest.

criterion : string, optional (default="gini")

The function to measure the quality of a split. Supported criteria are "gini" for the Gini impurity and "entropy" for the information gain. Note: this parameter is tree-specific.

max_features : int, float, string or None, optional (default="auto")

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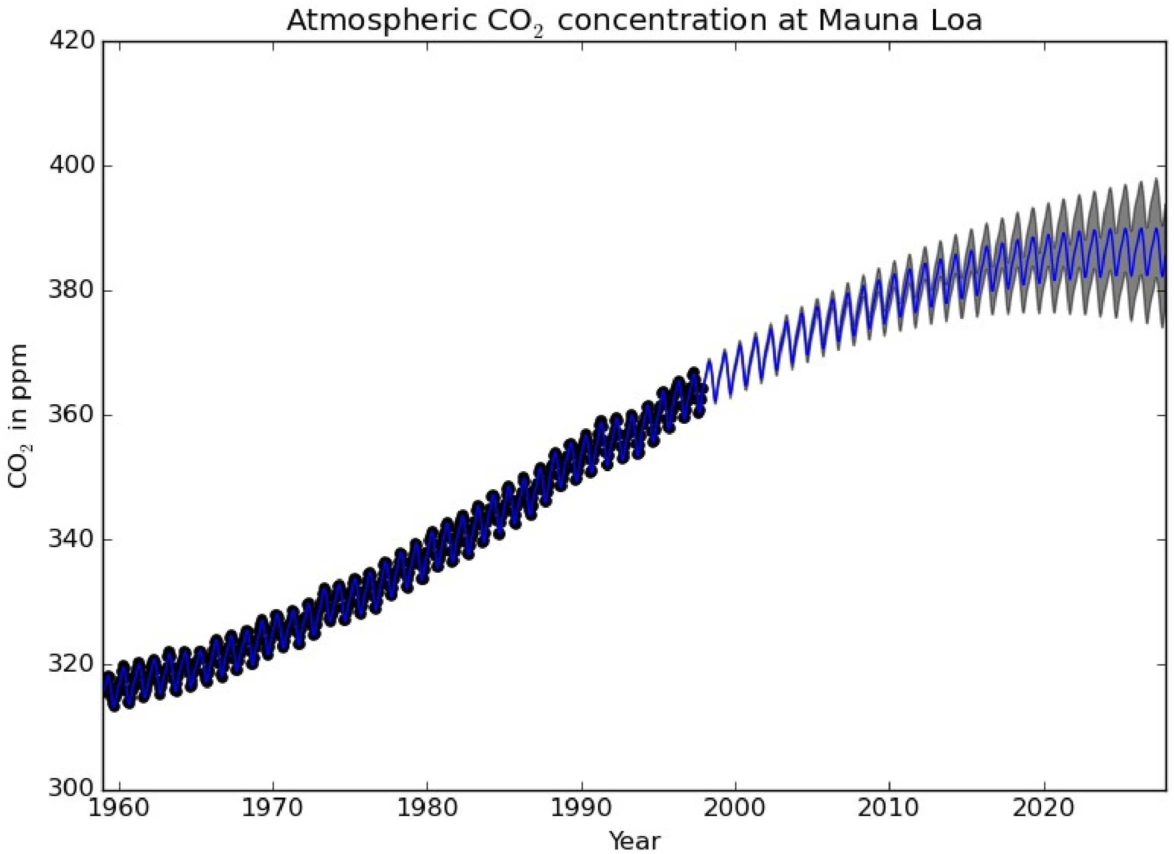
max_features : int, float, string or None, optional (default="auto")

What the future will bring (0.18)

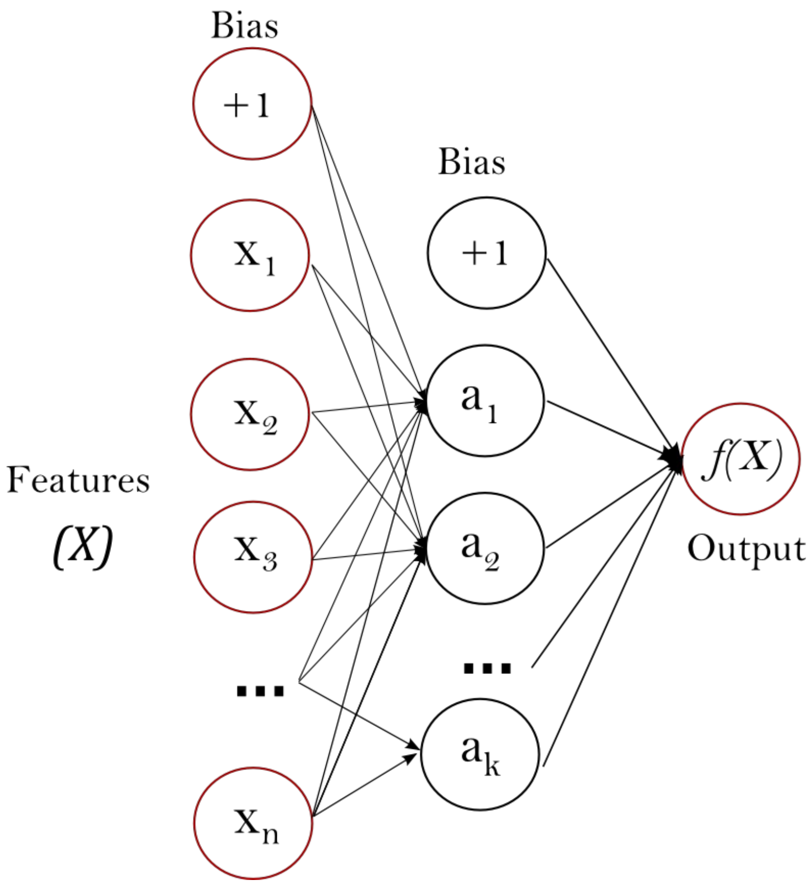
Gaussian Process Rewrite

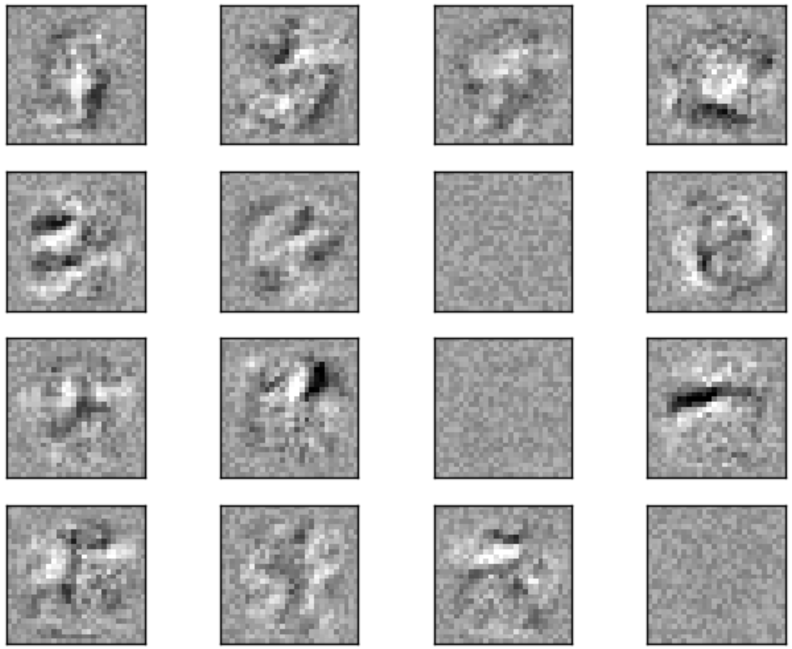



```
34.4**2 * RBF(length_scale=41.8)
+ 3.27**2 * RBF(length_scale=180)
   * ExpSineSquared(length_scale=1.44, periodicity=1)
+ 0.446**2 * RationalQuadratic(alpha=17.7, length_scale=0.957)
+ 0.197**2 * RBF(length_scale=0.138) +
WhiteKernel(noise_level=0.0336)
```

By Jan Hendrik Metzen.

Neural Networks





By Jiyuan Qian and Issam Laradji

Improved Cross-Validation

current

```
>>> import numpy as np
>>> from sklearn.cross_validation import KFold

>>> kf = KFold(4, n_folds=2)
>>> for train, test in kf:
...     print("%s %s" % (train, test))
[2 3] [0 1]
[0 1] [2 3]
```

future

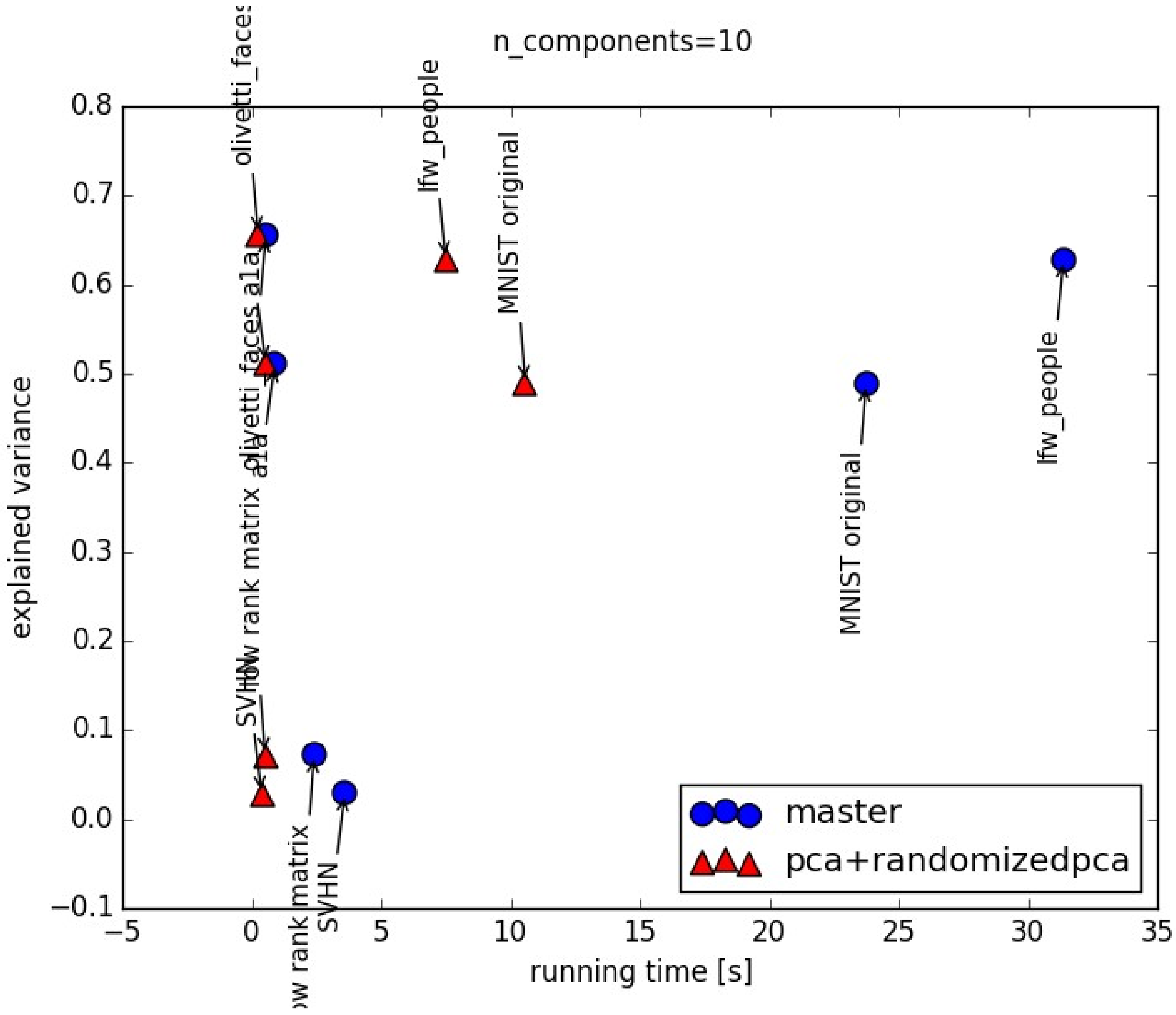
```
>>> import numpy as np
>>> from sklearn.model_selection import KFold

>>> X = ["a", "b", "c", "d"]
>>> kf = KFold(n_folds=2)
>>> for train, test in kf.split(X):
...     print("%s %s" % (train, test))
[2 3] [0 1]
[0 1] [2 3]
```

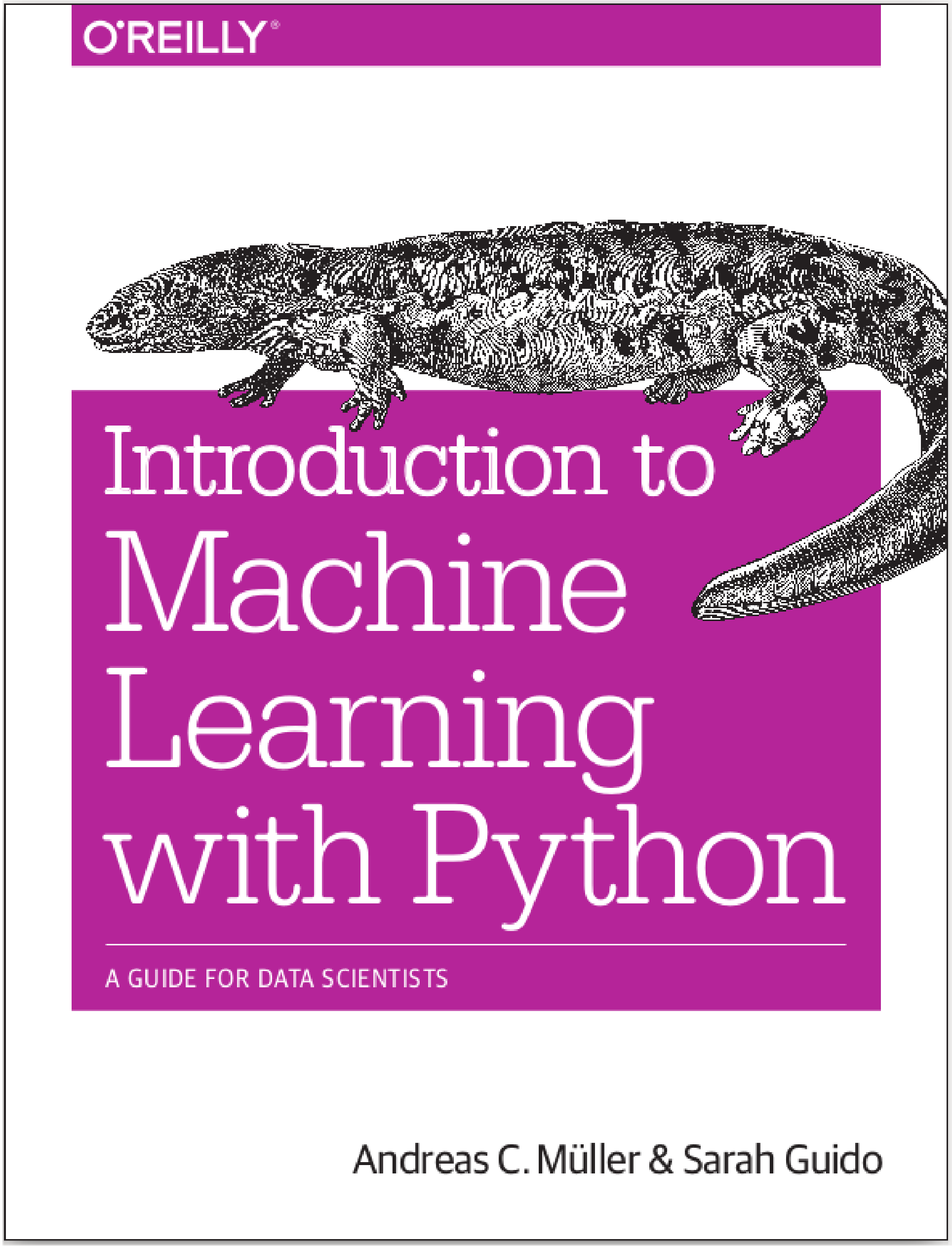
```
gs = GridSearchCV(LinearSVC(random_state=0), param_grid={'C': [1, 10]},
                  cv=inner_cv)
cross_val_score(gs, X=X, y=y, labels=labels, cv=outer_cv,
                fit_params={'labels': labels})
```

By Raghav RV

Faster PCA

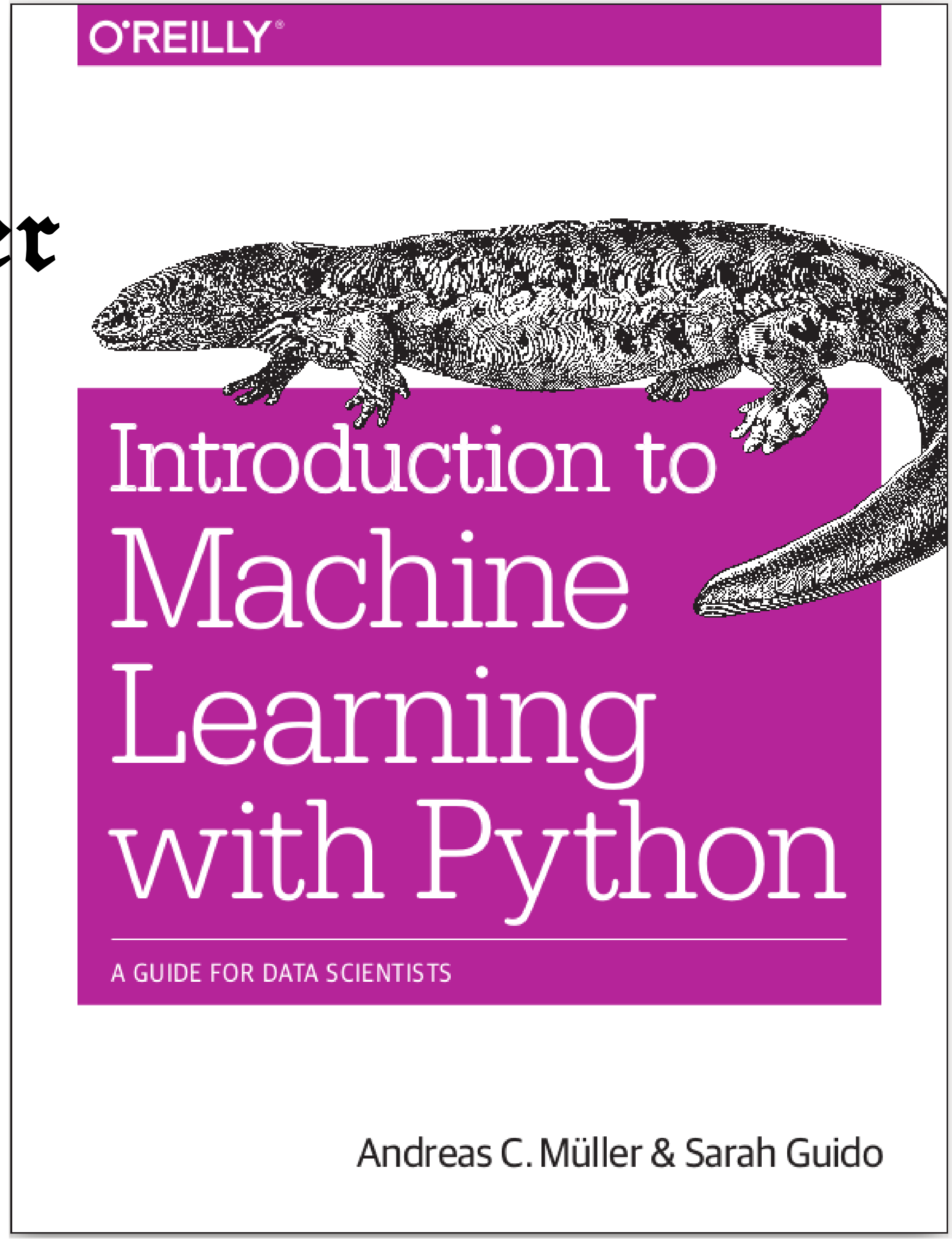


By Giorgio Patrini



Release June 2016

Hellbender



Release June 2016

Thank you!

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http://amueller.github.io